Big Tech, Financial Intermediation and the Macroeconomy*

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Abstract

The entry of big tech firms into financial services, particularly credit provision, presents challenges for central banks. We first examine the rapid expansion of big tech credit in some jurisdictions and highlight its distinctive features compared to traditional bank lending, emphasising differences in funding structures. We then evaluate the macroeconomic relevance of big tech credit through the lens of a stylized model where big tech facilitates firms' matching on the e-commerce platform and extends loans, enforcing repayment with the threat of exclusion. Our model suggests that: (i) an increase in the efficiency of big tech raises the value for firms of trading on the platform and the availability of big tech credit, with the positive impact on output being limited by the distortionary nature of the fees; (ii) big tech credit mitigates the response of output to a monetary shock but the mitigation depends inversely on the platform's matching efficiency; (iii) big tech credit acts as a 'spare tyre' in the face of adverse financial shocks.

JEL classification: E44, E51, E52, G21, G23
Keywords: Big tech, monetary policy, credit frictions, financial stability

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1 Introduction

New technologies are rapidly transforming the financial landscape. Since the Global Financial Crisis, regulatory changes and advances in artificial intelligence have led to a substantial increase in the market-share of nonbanks, including companies specialised in technology-enabled financial services (fintech) and large technology firms (big tech). While fintech companies are set up to operate primarily in financial services, big tech firms - such as Alibaba, Amazon, Facebook or Mercado Libre - offer financial services as part of a much wider set of activities, predominantly oriented towards information technologies and data consulting. Big tech firms typically exploit synergies and data collection across the different activities to further expand their business. Using machine learning and big data, these firms can assess the repayment history and credit-worthiness of trading clients in real time, and more precisely than traditional commercial banks (e.g. Bazarbash (2019), Frost et al. (2019)).

Improved data availability and massive technological advantages have led big tech firms to expand their activities in the financial services industry. Big tech's initial focus on payment services has progressively extended into services related to wealth management, consumer credit and lending to small and medium enterprises. Over the last decade, fintech and big tech credit have jointly increased their relevance as sources of non-bank funding. The amount of credit extended globally increased from the USD 20 billion in 2013 to USD 756 billion in 2019. Fintech credit amounted to almost the totality of this amount until 2016, but big tech credit has increased its share over time. In 2019, big tech credit flows overcame fintech flows, becoming twice as large. Furthermore, the pace of increase in big tech credit has exceeded that of bank credit in some countries. For instance, during 2022-23, big tech credit in China recorded an average annual growth rate of 35%, compared to 6% for bank credit.

The relevance of these alternative forms of credit is highly heterogeneous across countries. In 2015, lending volumes were negligible globally. Since then, big tech credit has remained of limited importance in the US but has become quantitatively relevant in China, Kenya and Indonesia (Cornelli et al. (2022)). China is a striking example of rapid expansion. Big tech credit flows increased from around zero in 2015 to 4% of GDP by 2020. Furthermore, estimates based on major big tech firms indicate credit flows of around 7.5% of GDP in 2023. One major reason for the limited relevance of big tech's lending activity in the US is stringency of regulation. Online lending must comply with federal and state laws, which limit big tech firms from obtaining a banking charter (Barakova et al. (2024)). This is an impediment to the extension of credit by the big tech if not in partnership with a bank. Regulation in China differs as it restricts big tech firms from holding a controlling share in digital banks but does not prevent them from extending credit.

This paper explores the challenges that big tech's financial intermediation poses to central banks, especially concerning economic activity, monetary policy transmission, and financial stability.

We first highlight the growing role of big tech companies in the financial system. We describe the recent expansion of their activities across borders and business lines. We then examine their provision of financial services and how they interact with banks in offering these services. We describe in particular their lending activity and the distinguishing features compared to banks' credit extension. Furthermore, we document the funding structure of big tech firms, considering their limited access to deposit financing, and the extent to which they employ the originate-to-distribute model. Finally, we highlight the risks to financial stability that can emerge from both their financial and non-financial activities.

We then provide a model-based evaluation of the macroeconomic relevance of big tech's financial intermediation activity. We assess the possible impact of big tech credit on real activity in the long run, how it may affect the transmission of monetary policy, and the role it can play in shielding the economy from adverse financial shocks. We do this through the lens of a stylized model that captures some key features of big tech's complex structure. The model is characterized by credit frictions in the production sector, search and matching of intermediate and final goods firms on an e-commerce platform, and nominal wage rigidities. The big tech plays a double role: it facilitates the search and matching between trading firms, and extends working capital loans to clients operating on their platform. Intermediate goods firms may finance their working capital with both secured bank credit and big tech credit, but cannot commit to repay their loans. The crucial difference between big tech credit and bank credit relates to borrowers' opportunity cost of default. Firms that default on bank credit lose a share of their real estate collateral. Those that default on big tech credit lose access to big tech's e-commerce platform, and hence a share of their future profits from trading on that platform.

We calibrate the model on US data. The baseline economy is therefore one where the share of big tech credit is approximately zero and the only available funding source is bank credit. We then analyse alternative economies where the share of big tech credit is progressively increased. The model delivers three main sets of results.

First, an expansion in big tech's activities, as captured by a rise in matching efficiency on the e-commerce platform, increases the value for firms of trading on the platform and the availability of big tech credit. This in turn relaxes financing constraints and raises firms' output, driving production closer to its efficient level. The efficiency gains are nonetheless limited by the distortionary nature of the fees collected from platform users. Specifically, as most big tech fees are proportional to transactions on the platform, they act as sales taxes and distort the equilibrium allocation.

Second, under a calibration where big tech's matching efficiency on the e-commerce platform is relatively low and big tech credit is sufficiently large, big tech credit reacts less than bank credit to monetary policy shocks. This is due to a more muted response of firms' opportunity cost of default on this new type of credit (future profits) compared to that on bank credit (real estate collateral). Thus, at relatively low matching efficiency levels, this novel type of credit mitigates the transmission of monetary policy shocks to credit and output. However, the mitigation effect depends non-linearly on the matching efficiency of the e-platform. As this latter rises and the effect of matching frictions decline, network collateral becomes more sensitive to macroeconomic shocks and the mitigation effect of big tech credit weakens. Eventually, if the matching efficiency becomes sufficiently high to push the economy into its credit-frictionless region, the mitigating effect of big tech credit increases again as the financial accelerator fades away and the sensitivities of total credit and real activity to aggregate shocks drop sharply.

Third, the entry of big tech in financial intermediation can contribute to financial stability by shielding the economy from the impact of adverse financial shocks that reduce the supply of bank credit. By mitigating the impact of the shock on the price of capital and its collateral value, the availability of big tech credit reduces the negative impact of the adverse financial shock on bank loans and provides a 'spare tyre' for the economy, preventing a larger contraction of total credit and real activity.

Our paper relates to the literature that emphasizes the role of physical collateral in the amplification of macroeconomic fluctuations (e.g. Gertler and Gilchrist (1994), Kiyotaki and Moore (1997), Iacoviello (2005)), particularly as a driver of the Great Depression (Bernanke (1983)) and of the more recent financial crisis (Mian and Sufi (2011), Bahaj et al. (2022), Ottonello and Winberry (2020) and Ioannidou et al. (2022)). It also connects to the literature on the role of intangible collateral (e.g. Amable et al. (2010), Nikolov (2012)), as well as of earnings-based borrowing constraints (e.g. Drechsel (2023), Drechsel and Kim (2024), Ivashina et al. (2022), Lian and Ma (2021), Holmstrom and Tirole (1997)). One distinguishing feature of borrowing limits on big tech credit compared to those imposed by earnings or intangible collateral is their link to the matching efficiency on the e-commerce platform. The ability of big tech to enforce repayment with the threat of exclusion from the e-commerce platform also relates to a recent literature that evaluates the role of trade credit in amplifying financial shocks (Bocola and Bornstein (2023), Cunat (2007), Altinoglu (2021), Luo (2020). Trade credit is sustained in equilibrium by reputation as customers lose the relationship with their suppliers in case of default.

The paper further connects to a literature on financial innovation and inclusion. The empirical evidence suggests that fintech and big tech credit are growing where the current financial system is not meeting the demand for financial services (Bazarbash (2019), Haddad and Hornuf (2019), Croxson et al. (2023), Hau et al. (2021)). Beck et al. (2022) find that creating a digital payment footprint enables small firms to access credit from big tech companies, and that this has spillover effects for their ability to obtain bank credit. Similar findings are uncovered by Frost et al. (2019) using data from Mercado Credito, which provides credit lines to small firms in Argentina on the e-commerce platform Mercado Libre. In our setup, a rise in the efficiency of big tech in matching buyers and sellers on e-commerce platforms can lead to an overall expansion of credit supply along the intensive margin (the same firm is offered more credit) and the extensive margins (more firms receive credit).

We also contribute to a novel literature on the impact of new financial technologies on the transmission of monetary policy. In contrast to our paper, contributions to this literature have been so far empirical and focused on China. In particular, Hasan et al. (2023) estimate a panel-VAR with monetary policy shocks and regional macroeconomic data for China, and conclude that the provision of credit by AntGroup, the financial arm of the big tech company Alibaba, has relaxed firms' financial constraints, and has made real activity and inflation less sensitive to monetary policy. Huang et al. (2023) estimate that for firms already using actively both bank credit and big tech credit from AntGroup, the two types of credit are equally sensitive to the interbank rate. Using a broad measure of fintech/big tech credit in a cross-country panel-VAR analysis, Cornelli et al. (2024) find that these non-traditional forms of credit react less to monetary policy compared to traditional bank credit.

Finally, our paper contributes to the literature on how to regulate big tech. While the expansion of big tech into financial services can bring benefits, such as increased competition, efficiency and financial inclusion - particularly in emerging market and developing economies - it also rises to important policy concerns (Feyen et al. (2021)). Specifically, this expansion intensifies issues related to maintining a level playing field with banks, operational risks and too-big-to-fail scenarios (Carstens (2021), Restoy (2021)). Additionally, it presents challenges for antitrust regulations and consumer protection (Croxon et al. (2021)). At the same time, regulation can hinder big tech firms from offering financial services and impede information sharing with banks, resulting in inefficiently low credit provision (Brunnermeier and Payne (2024)).

The paper is organized as follows. Section 2 describes the growing role of the big tech industry in the financial system and highlights the main benefits and challenges, including those related to financial stability. Section 3 presents the model and the empirical evidence that guides our calibration strategy. Section 4 describes the main numerical results, illustrating the impact of big tech's intermediation activity on the macroeconomy, the transmission of monetary policy and financial stability. Section 5 concludes.

2 Big tech and the evolving financial system

Over the past decade, big tech companies have significantly expanded their involvement in the financial sector.[1] We present here evidence on their business growth across various activities and countries, examining revenue shares and geographical concentration. We also explore how these relate to the big tech balance sheet structures. In particular, we discuss the sources of big tech funding, in light of the limited access to deposit financing, and the extent to which big tech employs the originate-to-distribute model.

[1]For more details on the definition of Big Tech firms see https://www.fsb.org/uploads/P091219-1.pdf.

2.1 Big tech's expansion across borders and business lines

Global e-commerce sales have risen rapidly (Figure 1, panel a). Online orders increased from $1.5 trillion in 2017 to $3.6 trillion in 2022, amounting to nearly 3.6% of global output. The global share of retail e-commerce sales in total retail sales rose from 12% in 2018 to 20% in 2023 (panel b). In China, this share increased over the same period from about 30% to more than 45%. On average, during the period 2017-19, around 84% of global online transactions were among firms - that is, business-to-business (B2B) transactions (panel c).

(a) Online orders in retail industry in selected countries

(b) Retail e-commerce sales

(c) Share of B2B and B2C in global e-commerce sales

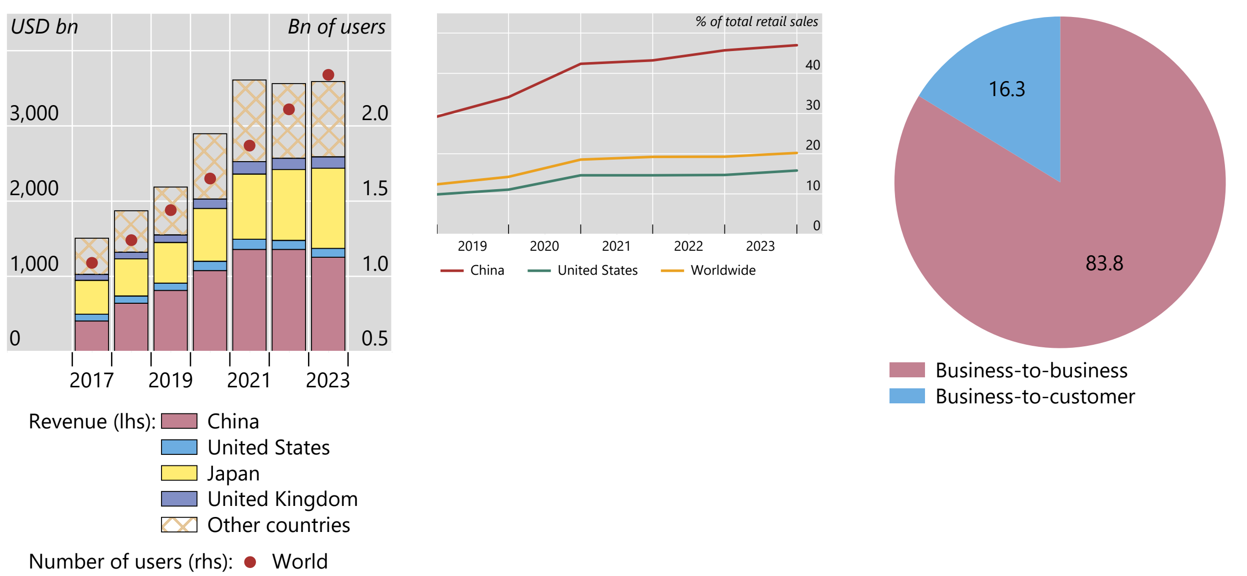

Figure 1: Rising global e-commerce sales

Notes: Sources: UNCTAD; eMarketer; Statista; authors' calculations.

Big tech's core business is in information technology, accounting for more than 48% of total revenues (Figure 2, panel a). Other relevant activities are communication services, which amounts to 24% of total revenues, and consumer goods, which amounts to another 22%. Financial services are still a small share of the overall activities, representing only 4% of total revenues in 2022. While big tech serves users globally, their headquarters and operational subsidiaries are mainly located in Asia and the Pacific, and North America (panel b).

Due to their scale of operations and scope of business, big tech companies have established a significant global presence. By exploiting data on the downloads of apps they have developed, we can shed light on the geographic distribution of new users, notably by measuring adoption at the extensive margin. Big tech products have been used widely across both advanced and emerging market economies. Jurisdictions where big tech companies are headquartered have seen stronger adoption rates, but adoption in other regions is also significant. Measuring adoption as the cumulative number of downloads of apps offered by big techs over the period 2012–June 2024 and normalized by population, we find that, on average, a resident in China, Hong Kong SAR, Korea, Saudi Arabia, or the United States has downloaded more than 35 apps from big tech companies. This figure is around 30 apps in countries such as Australia, Brazil, and the United Kingdom.[2]

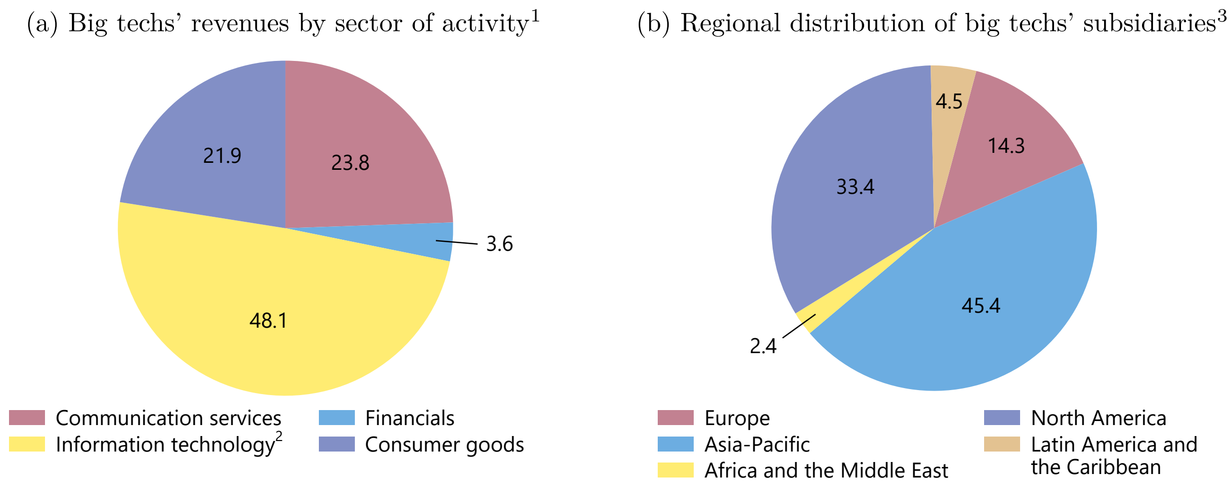

Figure 2: Big tech business and regional distribution

Notes: The sample includes Alibaba, Alphabet, Amazon, Apple, Baidu, Facebook, Grab, Kakao, Mercado Libre, Rakuten, Samsung and Tencent. [1] Shares based on 2022 total revenues as provided by SP Capital IQ. [2] Information technology can include some financial-related business. [3] Shares are calculated on the number of subsidiaries as classified by SP Capital IQ. Sources: S&P Capital IQ; BIS calculations.

International adoption, measured as the share of app downloads from countries different from where the big tech is headquartered, has also increased significantly. For the median big tech company, this share rose from 40% in 2012 to more than 60% in 2023 (Figure 3, panel a). Comparing these figures with those for other global institutions, such as Global Systemically Important Banks (GSIBs), highlights the substantially higher degree of internationalization of big tech companies.

[2]The sample includes apps published by Airtel, Alibaba, Amazon, Apple, BKash, Baidu, Gojek, Google, Grab, Jumia, KDDI, Kakao, Kakao bank, M-Pesa, MTN, MercadoLibre, Meta, Microsoft, Ola, Orange, Ovo, Ozon, Rakuten, STC, Samsung, Telenor, Tencent, Tokopedia, Toss, Uber and Yandex. Data for mainland China are estimated based on the downloads from the Apple- and the GooglePlay store, and the share of users with an Android operating system who likely download apps from stores other than the two covered by Sensor Tower. Data source: Sensor Tower and Statista.

Over the same period, the international adoption rate for the median GSIB remained roughly constant at around 10%. Finance apps offered by big tech companies have witnessed an even more striking growth in international adoption. For the median big tech company, this metric grew fourfold - from around 10% in 2012 to about 40% in 2023. Adoption records a remarkable growth also in the size of the big tech user bases (panel b). In 2023, the average number of monthly downloads for big tech apps exceeded one million, compared to the initial number of 200,000 in 2012. Notably, the number of downloads of finance apps has grown even faster, particularly since 2017.

(a) Big tech international presence over time[1] (b) Adoption of big tech products[2]

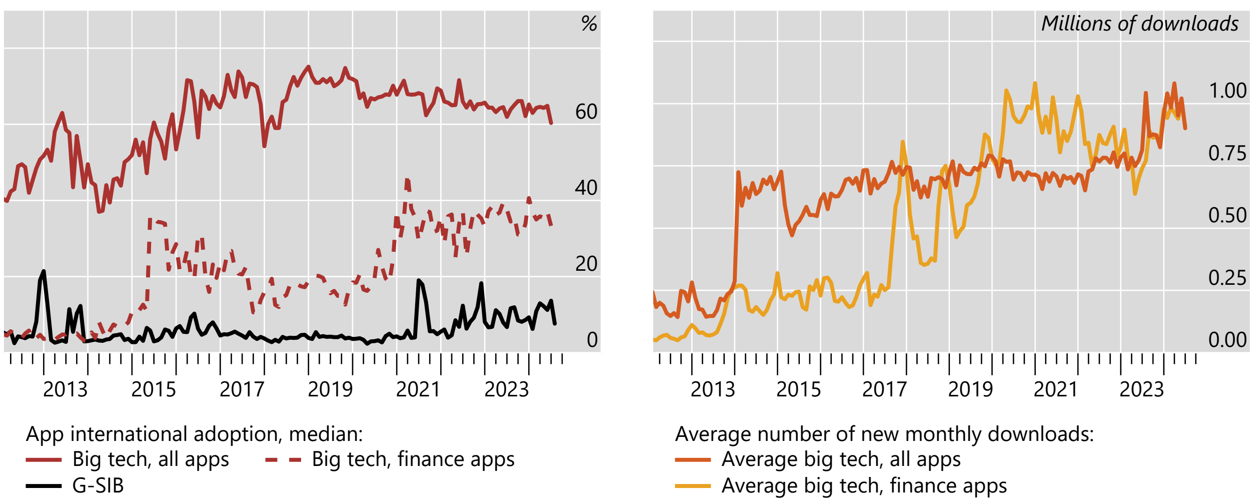

Figure 3: Big tech's adoption

Notes: [1] International adoption is defined as the share of app downloads from countries different from the one of the big tech offering the app. [2] The lines show the number of monthly downloads of all the apps published by a big tech divided by the total number of apps that it offers for the average big tech. [3] The sample includes apps published by Airtel, Alibaba, Amazon, Apple, BKash, Baidu, Gojek, Google, Grab, Jumia, KDDI, Kakao, Kakao bank, M-Pesa, MTN, MercadoLibre, Meta, Microsoft, Ola, Orange, Ovo, Ozon, Rakuten, STC, Samsung, Telenor, Tencent, Tokopedia, Toss, Uber and Yandex. Sources: Sensor Tower; authors' calculations.

2.2 Big tech's financial services and interactions with banks

Financial services remain a small share of big tech business, but demand for these services is growing faster than for other big tech products, as witnessed by the rapid increase in downloads of finance apps. Moreover, the demand for financial services has diversified over time. We gauge this demand by computing the average number of downloads per big tech app in each period and for each sub-category (Figure 4). Until 2018 payment apps constituted the bulk of finance apps downloads. In the most recent period, however, the share of new downloads of payment apps has decreased steadily and significantly – by one third – in favour of apps for consumer banking, investing and financial management, and personal finance. Among these financial activities, the largest expansion is observed in investing and financial management apps, which increased from 3% to nearly 20%. This trend mirrors the business model of big tech companies. Typically, these firms entered the finance sector by offering payment services, through which they gathered data and information about customers. They then leveraged these data to offer additional financial products, such as credit and financial management, which commonly require some degree of profiling.

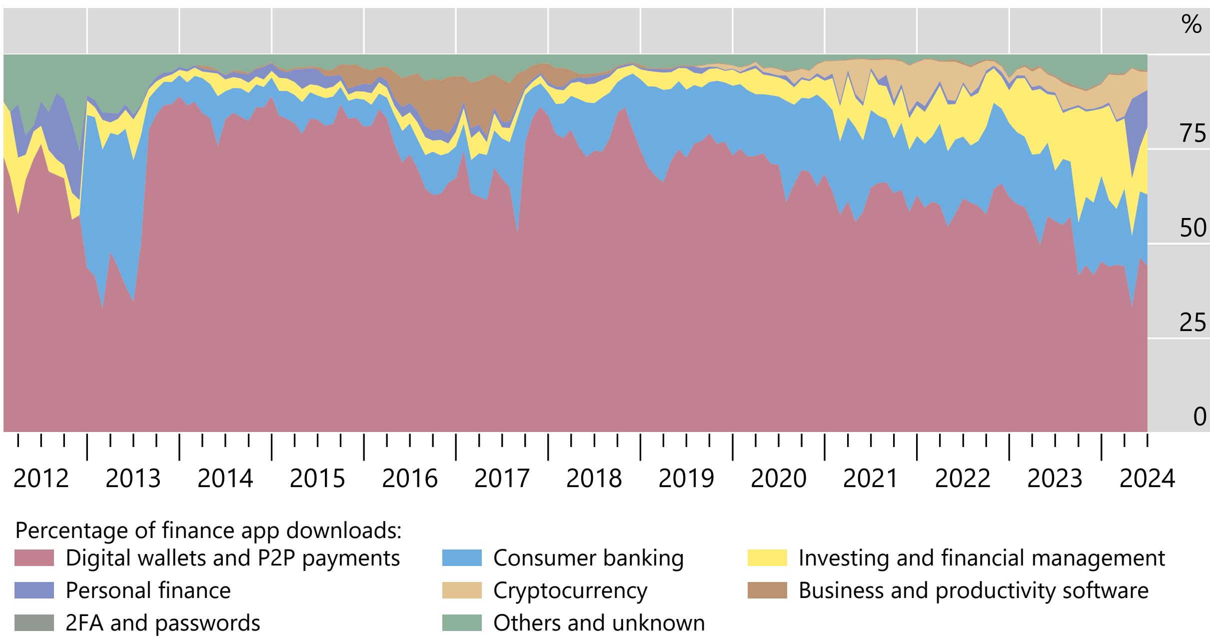

Figure 4: The demand of big tech finance apps

Notes: Based on the average number of downloads per app in each period and for each sub-category of finance apps. 'Others' includes fast food and fast casual restaurants, news and magazines and telecoms. 'Unknown' corresponds to finance app for which Sensor Tower doesn't provide a sub-category. Sources: Sensor Tower; authors' calculations.

Among financial services, money market funds (MMFs) offered through big tech platforms have grown substantially, most prominently in China. At the end of 2023, total MMFs affiliated with big tech amounted to about 23% of outstanding wealth management products. Some big tech firms have also started offering insurance products, using their platforms mainly as a distribution channel for third-party products. In the process, these firms collect customer data, which they combine with other information to help insurers improve their marketing and pricing strategies.

	Main geographical area of activity	Payments	Money market funds and insurance	Credit
Emerging market economies				
Alibaba/Alipay, Tencent	China	△	△/✓	△
Baidu	China	△	△/✓	✓
Vodafone M-Pesa	East Africa, Egypt and India	△		✓
Mercado Libre	Argentina, Brazil and Mexico	△		△
Samsung	Korea	✓		
GO-Jek, Ola Cabs	Southeast Asia	△		
Grab	Southeast Asia	△	✓	△
KT	Korea	✓	△	△/✓
Kakao	Korea	△/✓		△/✓
Advanced economies				
Google	Worldwide	✓		△/✓
Amazon, eBay/PayPal	Worldwide	✓		✓
Apple, Facebook, Microsoft	Worldwide	✓		✓
Orange	France	✓		✓
Groupon	Worldwide	△		
Line, Rakuten	Japan	△	△	△
NTT Docomo	Japan	△	△	✓

Table 1: Financial activities of selected big tech firms

NOTE: △ indicates new entities and operations introduced outside the traditional financial and banking network. ✓ indicates the provision of services as overlays on top of, or in collaboration with, existing financial institutions (especially banks and credit card providers). Sources: Financial Stability Board; S&P Capital IQ; public sources; BIS.

In offering financial services, big tech both competes and cooperates with banks.Thus far, big tech has focused on providing basic financial services to the large network of customers and has acted as a distribution channel for third-party providers, eg by offering wealth management or insurance products. As shown in Table 1, services provided under each category - payments, MMF and insurance, and credit - are offered either independently from or in collaboration with banks, depending on the specific big tech firm.

2.3 Big tech credit

Big tech credit has rapidly expanded in the pre-Covid period, reaching global volumes of USD 530 billion in 2019, up from only around USD 11 billion in 2013. In more recent years, the growth rate of big tech credit has further increased, exceeding that of bank credit in several countries. Estimates for 2021-2023 based on three big tech firms, which accounts for around half of the big tech credit flows in China in 2020, indicate that these flows may have reached 7.5% of GDP in 2023 (Figure 5).

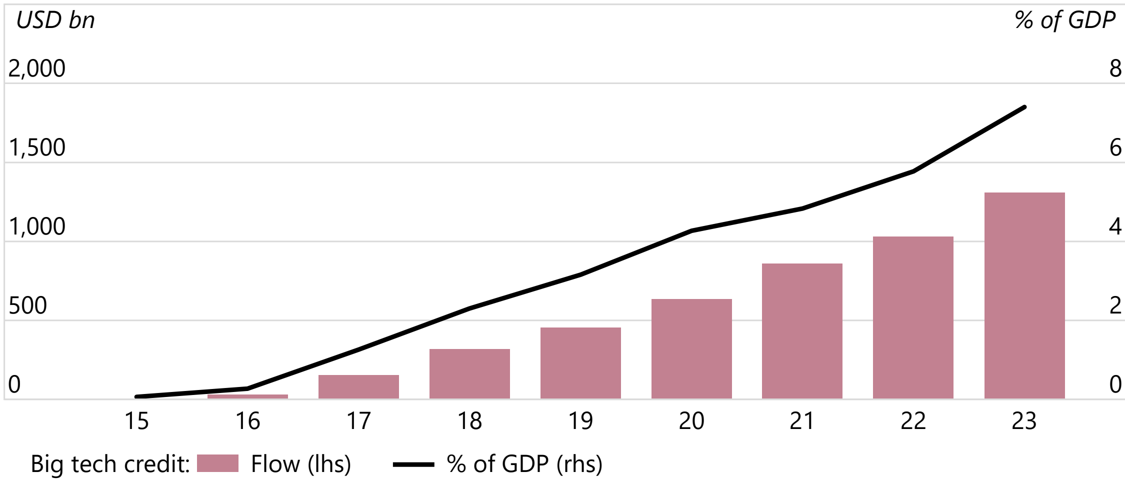

Figure 5: Big tech credit has been growing fast in China

Notes: The figure shows the evolution of big tech credit in China. The bars report the yearly flow (left scale), while the line report the flow as a percentage of GDP (right scale). The data for the period 2015–20, is based on confidential entity-level data received from the central bank for five big tech companies. Due to data availability, data for the period 2021–23 is estimated based on the rate of growth of the lending flow by a subset of three big tech companies which corresponded to about one-half of the total lending volume in 2020 and disclose information on their lending activity publicly. Source: Cornelli et al. (2023); company filings; authors' calculations.

Big tech credit differs from bank credit along several dimensions. It is not secured against physical collateral and has shorter maturity than bank credit. In China, around two-thirds of big tech credit has an average maturity of less than one year and is typically renewed several times, as long as the credit line remains in place (Beck et al. (2022)). In contrast, only 43% of bank credit has maturity below one year. Similar characteristics are detected outside China; for instance, Mercado Libre in Mexico exhibits comparable patterns (Frost et al. (2019)).

Using micro data for Chinese firms for the period 2017-19, Gambacorta et al. (2022) document that big tech credit does not correlate with local business conditions and house prices when controlling for demand factors; instead, it reacts strongly to changes in firm characteristics, such as transaction volumes and network scores used to calculate firm credit ratings. By contrast, both secured and unsecured bank credit react significantly to local house prices, which incorporate useful information on the environment in which clients operate and their creditworthiness. We extend their analysis to macroeconomic data for China and the US, covering a more extended period of time, ie 2013-2020. As shown in table 2, our results confirm their findings. In both regions, bank credit is more correlated to house prices than big tech credit, whereas the opposite is true for e-commerce sales.

	China	United States
Big tech credit to house price	0.56	0.18
Bank credit to house price	1.40***	1.02***
Big tech credit to e-commerce sales	5.39***	3.75***
Bank credit to e-commerce sales	0.39***	0.25***

Table 2: Credit elasticity to house prices and to e-commerce sales

Notes: Unconditional elasticities. Estimation period 2013-2020. *** Significance at the 1% level. Sources: data on big techs are from Cornelli et al. (2023), on e-commerce sales are from Statista and on house prices are from the BIS.

Big tech's rapid expansion in credit provision mirrors its revenues. Due to large profits, big tech firms have a substantial amount of liquidity they use to finance lending to firms and consumers. Boissay et al. (2020) show that big tech firms are more profitable and better capitalised than global systemically important financial institutions (G-SIFIs) and have a larger amount of assets in liquid form. Prior to the Covid shock, the average earning-to-asset ratio for big techs was 24%, against 4% for G-SIFIs. The larger amount of profits was also reflected in a higher equity-to-total asset ratio (52% against 8%) and cash-to-total asset ratio (11% against 7%).

				Fixed	Variable		
E-commerce platform	Fixed Fee	Variable Fee	Other Fees	Average	Average	Min	Max
Amazon	$0-$39	6% to 45%, average seller pays 15% of selling price, varies with category of product	Amazon might charge if the seller uses its logistics services (minimum of $3.43), also sometimes pays a shipping credit	19.5	15	6	45
AliExpress	0	5-10% of selling price, depends on product category	Offers shipping at additional costs, cheaper than other shipping services but longer delivery times	0	7.5	5	10
Shopify	$5 to $299	2.4% to 5% + 30c per sale		150	3.7	2.4	5
E-bay	First 250 items free, then $0.35 per item	2% to 12.25% of total price (selling price + shipping, handling cost)		0	7.25	2	12.5
Etsy	$0.20 per item	6.5% of total price (selling price + shipping, handling costs)	Etsy Plus subscription at $10 a month	0	6.5	6.5	6.5
Walmart	0	6% to 15%		0	10.5	6	15
					8.4	2	45

Table 3: E-commerce platform fees

NOTE: authors' calculations based on data for 2022.

A substantial part of big tech revenues comes from fees that are charged for different services, including platform access fees for third-party merchants and consumers, subscription fees for premium services, and advertising fees for reaching a wider audience. E-commerce platform fees are typically divided in a fixed component and a variable one. The fixed fees cover a number of services provided by the platform for product advertisement. The variable fee is a percentage of the sale price charged by big tech firms to third-party merchants for using their platforms to reach customers. Table 3 reports the structure of the e-commerce platform fees for a selected number of big techs and shows that the average variable platform fee is around 8%.

Big tech credit exhibits lower default rates than bank credit. Table 4 compares non-performing loans (NPLs) for the average Chinese banks and for MYbank - a big tech firm that focuses on credit to small and medium-sized enterprises and accounts for around 50% of big tech lending in China. As reported in the first two rows of the table, NPLs for the Chinese banking industry have been substantially higher on average than those for MYbank in the period 2017-2023, including during the Covid-19 pandemic. These results are consistent with Huang et al. (2020), who find that big tech credit scoring yields better prediction of loan defaults both in normal times and in periods of large exogenous shocks, reflecting information and modelling advantages. Interestingly, the ex-post measure of credit risk is not mirrored in the interest rates that are substantially higher (on average) for big tech credit. Two main reasons may cause interest rates for big tech credit to be higher than those for bank credit. First, Chinese regulation does not allow big tech firms to open remote (online) bank accounts. This forces big tech firms to rely mostly on interbank market funding and certificates of deposit that are typically more costly than retail deposits (BIS, 2019), as we document below. Second, data processing for credit scoring could have high fixed costs to set up the necessary IT infrastructure and create a highly specialised team. These costs could be particularly high at the beginning, when the number of borrowers is low, and then decline with time, when the market share increases. Interestingly, this is reflected by the spread between big tech credit and bank credit interest rates that was around 11.2% in 2017, when MYbank started to offer credit to QR code merchants, and only 3.5% at the end of 2023.

	Credit quality SMEs: NPL ratio		Average interest rates SMEs	
Year	Banks [1]	MYbank	Banks [1]	MYbank [2]
2017	5.85%	1.23%	6.55%	17.70%
2018	5.50%	1.30%	6.16%	13.39%
2019	3.22%	1.30%	6.70%	10.21%
2020	2.99%[3]	1.52%	5.88%[4]	9.03%
2021	-	1.53%	5.69%	9.23%
2022	2.18%[5]	1.94%	5.25%	7.74%
2023	-	2.28%	4.78%	8.24%

Table 4: Financial activities of selected big tech firms

NOTE: Non-Performing Loans (NPLs) indicate loans that are typically overdue from 90 days and more. See Interim Measures for the Risk Classification of Financial Assets of Commercial Banks. [1] Credit lines below 10 million Yuan (5 million in 2017 and 2018). [2] Data obtained from public balance sheet information dividing interest earned and total loans for SMEs. [3] As of August 2020. [4] January–November 2020. [5] As of April 2022. Source: CBIRC, Annual reports of MYbank.

2.4 Big tech's financing

Big tech's lending footprint has so far been constrained by the limited ability to fund through retail deposits. However, big tech firms have some options to overcome this constraint. One possibility is to establish an online bank, although in some countries, regulatory authorities restrict the opening of remote (online) bank accounts. For example in China, two major Chinese big tech banks (MYbank and WeBank) rely mostly on interbank market funding and certificates of deposit rather than on traditional deposits. These banks have started issuing "smart deposits" that offer significantly higher interest rates than other time deposits and the possibility of early withdrawal at a reduced rate. A second option is to partner with a bank. Big techs can provide the customer interface and enable quick loan approval using advanced data analytics; once approved, the bank is left to raise funds and manage the loan. This arrangement is attractive to big tech firms because their platforms are easily scalable at low cost and they interact directly with clients. It can also be profitable for banks, as they can earn additional returns. A third option is to obtain funds through loan syndication or securitisation. For instance, Ant Financial's gross issuance of exchange-traded asset-backed securities (ABS) accounted for almost one third of total securitisation in China in 2017.

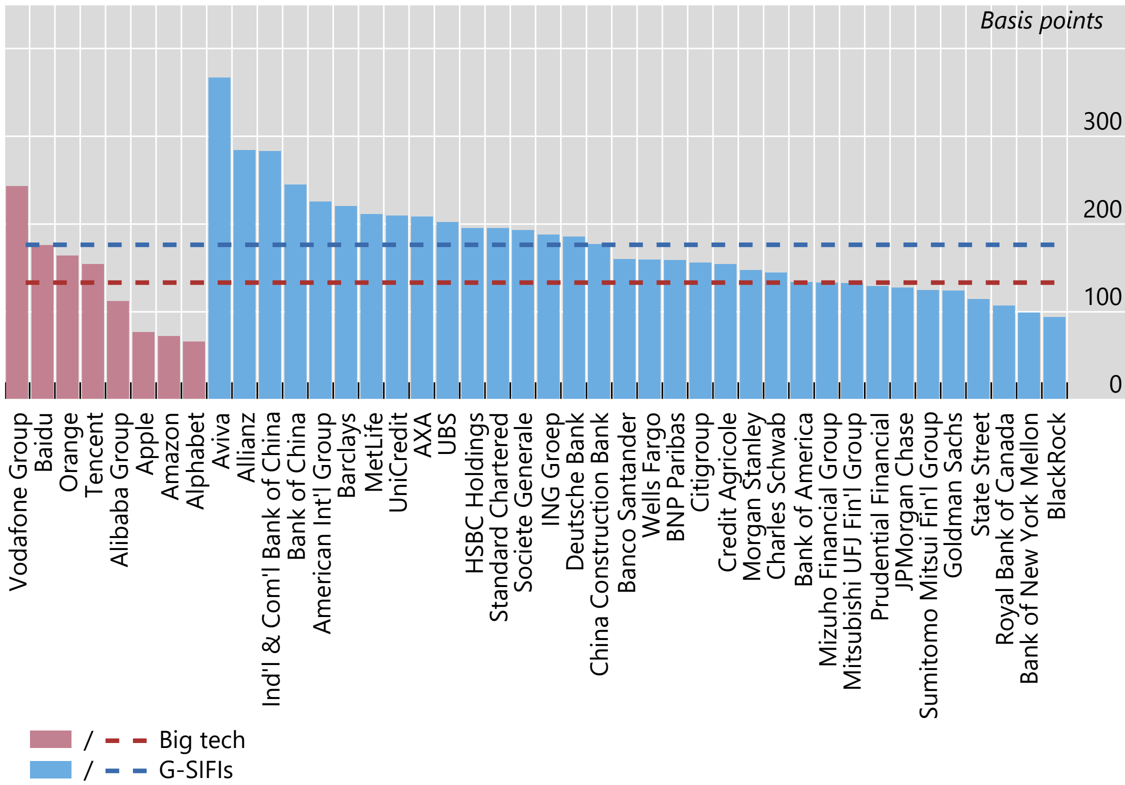

Figure 6: Average spread of active bonds to benchmark government bond at issuance

Notes: The dashed horizontal lines indicate the simple average. Average spread of active bonds over the respective benchmark government bond at issuance as collected by the Bloomberg SRCH function. Terminal accessed on 17 July 2024. Filters used: Corporates, Active, Issue date greater than 31/12/2018 and Issuer Name as listed in the graph. Sources: Bloomberg; authors' calculations.

While big tech firms need to replace cheap deposit-based funding with generally more expensive alternatives, they have a significant advantage in raising capital through bonds and equity, as they are perceived as large and highly profitable entities. Their size and diversified activities reduce risk and enhance the liquidity of their funding instruments, providing them with an advantage when issuing debt instruments. Therefore, when comparing similar funding components, such as bonds, big tech companies tend to have a significantly lower cost at issuance, as shown in Figure 6.

2.5 Big tech's risks and financial stability considerations

Big tech's entry into finance promises to enhance the efficiency of the financial sector, improving customer businesses and promoting financial inclusion. However, it may also create new risks associated with market power, data privacy, and financial stability (Boissay et al., 2021).

Platforms can exploit their market power and network externalities to increase user switching costs, exclude potential competitors, and consolidate their positions by raising barriers to entry. More relevant risks arise from market concentration and cyber attacks. One significant challenge emerges from the configuration of the big tech supply chain, which is creating concentration risks at the technology services level that need to be monitored from both competition and systemic stability perspectives. For example, the growing reliance of the financial sector on a small number of big tech companies that offer cloud services creates potential single-point-of-failure (FSB 2019). Notably, four big tech players control nearly three-quarters of the global market for cloud services.[3] This trend is consolidating and possibly accelerating over time, insofar the market share controlled by the four most influential players grew 6 percentage points from Q4 2019 (65%) to Q1 2024 (71%).

While big tech firms providing cloud services generally have deep expertise in systems architecture and cyber security, an operational or cyber incident at one major cloud provider could have systemic implications for the financial system (Danielsson and Macrae, 2020).[4] Open infrastructure, including API hubs, KYC utilities, and changing access policy for existing payment systems and credit reporting infrastructures, can mitigate concentration risks, increase contestability, and dilute data concentrations.

These new risks highlight the need for regulation of the big tech industry. Prudential regulators have turned their attention to specific market segments, notably in the payment system, where big techs have already become relevant from a systemic perspective in some jurisdictions.[5] Where rapid structural change has outrun the existing letter of the regulations, a revamp of those regulations will be necessary. In China, for instance, big tech's sizeable MMF businesses play an important role for interbank funding. [6] These MMFs mainly invest in unsecured bank deposits and reverse repos with banks. The rapid structural change has introduced new linkages in the financial system. In the first quarter of 2024, around 80% of MMFs' assets were invested in bank deposits and interbank loans with a maturity of less than 30 days. A redemption shock to big techs' MMF platforms could quickly transmit to the banking system through deposit withdrawals.

[3] Figure based on revenues for Q1 2024. Source: Statista and Synergy Research Group.

[4] For instance, the CrowdStrike incident on 19 July 2024 caused hours of outages for banks, money managers and stock exchanges.

[5] For example, Alipay (launched in 2004) and WeChat Pay (launched in 2011) together accounted at the end of 2023 for 94% of the $16 trillion mobile payments market in China.

[6] Yu'ebao money market fund offered to Alipay users has grown into the world's largest MMF, with assets under management over CNY 1.4 trillion (USD 210 billion). It accounts for about 28% of China's MMF industry.

3 Macroeconomic impact of big tech credit: a model-based analysis

In this section, we focus on big tech's growing presence in financial intermediation. We evaluate the impact of big tech's credit provision through the lens of a dynamic general equilibrium model.[7] While stylized, the framework captures some key features of the big tech business model and the main differences between big tech credit and bank credit.

We use the model as a laboratory to ask three questions. What is the macroeconomic impact of big tech's entry in finance in the long run? How does big tech's credit provision affects the transmission of monetary policy? And does big tech credit amplify or mitigate the impact of adverse financial shocks?

3.1 The model

The economy is populated by a large number of identical households who consume, invest and work. Nominal rigidities take the form of sticky wages. There are two types of firms, intermediate goods firms which produce using labor and capital, and final goods firms (retailers) which use intermediate goods as inputs. The big tech facilitates transactions between intermediate goods firms and retailers, and extends credit to the former. Banks also provide loans to intermediate goods firms. The public sector is formed of a government which issues risk–free nominal bonds and a central bank which sets the nominal interest rate according to a simple Taylor rule.[8]

In the model, intermediate goods firms may finance their working capital with both secured bank credit and big tech credit, but cannot commit to repay their loans. The crucial difference between big tech credit and bank credit relates to borrowers' opportunity cost of default. Firms that default on bank credit lose a share of their real estate collateral. In contrast, those that default

[7] The model is an extended version of the framework developed in De Fiore et al. (2023). In particular, we enrich the model with a larger set of shocks, including demand, technology, monetary and financial shocks; we introduce a finite number of exclusion periods from the e-commerce platform in case of default on big tech credit; and we use a different monetary policy rule that includes interest rate smoothing. The calibration of the model also differs, resulting in an improved fit of the model to the data.

[8] See Cahuc et al. (2014) for a description of search and matching frameworks applied to labor markets, and Trigari (2009) and Galí (2010) for monetary (New Keynesian) models incorporating them. See De Fiore and Tristani (2013), Bernanke et al. (1999), Iacoviello (2005) or Manea (2020) for New-Keynesian models studying how credit frictions affect the transmission of monetary policy and of business cycle shocks. As in Manea (2020), since credit is only used to finance working capital, sticky wages are necessary for credit frictions to amplify the response of output to business cycle shocks, and hence, for the model to feature a financial accelerator. One could write a version of the model with sticky wages and prices, but that version will entail adding an additional sector of monopolistic firms setting prices subject to nominal rigidities or assuming Nash-Bargaining with staggered price setting in the intermediate goods market à la Gertler et al. (2008) or Gertler and Trigari (2009).

on big tech credit lose access to big tech's e-commerce platform, and hence lose a share of their future profits from trading on that platform. An incentive compatible contract thus limits the total amount of credit to the sum of pleadgeable physical and network collateral. Here we only describe the blocks of the model that relate to the big tech and the trading firms on the platform. Appendix A reports all the remaining model equations.

3.1.1 The big tech firm

The big tech firm runs an e-commerce platform which facilitates search and matching between sellers and buyers of intermediate goods, and provides credit to the sellers on the platform.

The big tech firm builds net worth N_t^b by levying fees from both sellers and buyers on the e-commerce platform. Specifically, intermediate goods producers that are not matched with retailers at time t (a measure I_t) post advertisements on the platform at a unit real lump-sum cost χ_m defined in terms of the bundle of final goods. Furthermore, those with a match (a measure A_t) pay a fee τ^* proportional to their sales on the platform $\frac{p_t^m}{P_t} y_t^m$, where y_t^m is the quantity of intermediate goods sold by an individual firm and p_t^m is the unit price of such goods. This implies a total real income for the big tech firm in period t from taxes levied on intermediate goods firms equal to $\chi_m I_t + \tau^* \frac{p_t^m}{P_t} y_t^m A_t$. Furthermore, each retailer from a continuum of size one pays a unit real fee equal to χ_r for each of its S_t searches for intermediate goods suppliers, with the fee defined in terms of the bundle of final goods. This results in an additional real income for the big tech firm in period t equal to $\chi_r S_t$.

The big tech firm is owned by the household. Each period, it pays a nominal lump-sum transfer to the latter equal to Υ_t^b and invests its net worth at the end of each period in nominal risk–free public bonds B_t^b. This results in the following accumulation of net worth,

$$N_t^b = N_{t-1}^b(1 + i_{t-1}) + \chi_m P_t I_t + \tau^* p_t^m y_t^m A_t + \chi_r P_t S_t - \Upsilon_t^b$$

where i_{t-1} is the net interest paid on public bonds issued in period $t-1$. Within each period, the big tech firm has the option to either keep funds idle until the bond market opens at the end of each period, or using them to extend intra-period loans at zero interest rate. For simplicity, we assume they prefer the latter option. The lump-sum transfer Υ_t^b is such that the net worth of the big tech firm is equal to the incentive-compatible credit that it is willing to extend, ensuring that the big tech firm is never financially–constrained. It follows that $\frac{N_t^b}{P_t} = \int_0^1 \mathscr{L}_t^b(i)di$, where $\mathscr{L}_t^b(i)$ is the real value of the incentive-compatible credit extended to the intermediate goods firm $i \in [0, 1]$.

3.1.2 Intermediate goods firms

There is a continuum of perfectly competitive intermediate goods firms indexed on the unit interval. Intermediate goods are produced with a Cobb Douglas production technology

$$y_t^m(i) = \xi_t(k_t^m(i))^\gamma(l_t^m(i))^{1-\alpha}, \quad i \in [0, 1], \tag{1}$$

where ξ_t is a technology shock evolving according to the process $log(\xi_t) = \rho_\xi log(\xi_{t-1}) + \epsilon_t^\xi$, with $\rho_\xi \in [0, 1]$. $k_t^m(i)$ is the capital stock used in production by intermediate goods firm i, $l_t^m(i)$ is a CES index of labor input made of all labor types j hired by the intermediate goods firm i at the aggregate wage rate W_t.[9] The production function is characterised by decreasing returns to scale, that is $\gamma + (1 - \alpha) < 1$.[10]

To sell their output, intermediate goods firms need to match with retailers on the big tech's e-commerce platform. Every period, some of the existing matches split with exogenous probability δ, while new ones form with endogenous probability $f(x_t)$ (characterized below). For this reason, at each date t, the economy is populated with two types of intermediate goods firms: those matched with retailers at time t and producing (a share A_t of "active" intermediate goods firms), and those without a match which do not produce and do not sell (a share $I_t = 1 - A_t$ of "inactive" ones). Intermediate goods firms found out in period $t - 1$ their active or inactive status in period t. Since all A_t intermediate goods firms active at date t produce the same quantity in equilibrium, we drop the index i while describing their individual behaviour. The unit price p_t^m and the quantity sold y_t^m by each of them are determined in a decentralized manner via period-by-period collective Nash bargaining between the firms and retailers which are in a match at time t.

Each active intermediate goods firm producing at time t takes an intra-temporal loan $\mathscr{L}_t$ to hire labor l_t^m at unit price W_t, and issues equity to buy capital k_t^m at unit price Q_t^k. For convenience,

[9] The CES index of labor input $l_t^m(i)$ and the aggregate wage rate W_t take the standard CES expressions $l_t^m(i) \equiv \left(\int_0^1 l_t^m(i,j)^{1-\frac{1}{\epsilon_w}}dj\right)^{\frac{\epsilon_w}{\epsilon_w-1}}$ and $W_t \equiv \left(\int_0^1 W_t(j)^{1-\epsilon_w}dj\right)^{\frac{1}{1-\epsilon_w}}$ where $l_t^m(i,j)$ denotes the quantity of type j labor employed by firm i in period t. The aggregate wage bill of any given firm can thus be expressed as the product of the wage index W_t and the firm's employment index $l_t^m(i)$: $\int_0^1 W_t(j)l_t^m(i,j)dj = W_t l_t^m(i)$.

[10] This implies increasing marginal costs for firms. Similarly, in the labor market search and matching framework worker's marginal disutility of labour (the correspondent of the marginal cost in our setup) is increasing in labor.

we assume that each firm issues a number of claims equal to the number of units of capital acquired $\mathscr{E}_t = k_t^m$, and pays the marginal return on capital as dividend. Under this assumption, the price of each equity claim Q_t^e equals in equilibrium the price of capital Q_t^k, namely, $Q_t^e = Q_t^k$.

Two value functions on the intermediate goods firms' side play an important role in the Nash bargaining process: (i) the value for an intermediate goods firm of being "active" ($\mathscr{V}_t^A$), namely of being in a match; and (ii) the value for an intermediate goods firm of being "inactive" ($\mathscr{V}_t^I$), namely of being looking for a match. The former equals:

$$\begin{aligned}\mathscr{V}_t^A \equiv &(1-\tau^*)\frac{p_t^m}{P_t}\xi_t (k_t^m)^\gamma (l_t^m)^{1-\alpha} - \frac{W_t}{P_t} l_t^m - \frac{Q_t^k}{P_t} k_t^m + E_t\Big\{\Lambda_{t,t+1}\Big(\frac{Q_{t+1}^k}{P_{t+1}} k_t^m\Big)\Big\} + \\ &+ E_t\Big\{\Lambda_{t,t+1}\Big[(1-\delta)\mathscr{V}_{t+1}^A + \delta \mathscr{V}_{t+1}^I\Big]\Big\} \end{aligned} \tag{2}$$

where $E_t\Big\{\Lambda_{t,t+1}\Big[(1-\delta)\mathscr{V}_{t+1}^A + \delta \mathscr{V}_{t+1}^I\Big]\Big\}$ is the expected value of staying in the platform for an active firm at $t+1$, when with probability $1-\delta$ will maintain its match and gain $\mathscr{V}_{t+1}^A$, and with probability δ will lose the match and gain $\mathscr{V}_{t+1}^I$ instead. The value for an intermediate goods firm of being inactive at time t equals

$$\mathscr{V}_t^I \equiv -\chi_m + E_t\Big\{\Lambda_{t,t+1}\Big[f(x_t)\mathscr{V}_{t+1}^A + (1-f(x_t))\mathscr{V}_{t+1}^I\Big]\Big\} \tag{3}$$

where $-\chi_m$ are the net period losses incurred as it posts the advertisement, while $E_t\Big\{\Lambda_{t,t+1}\Big[f(x_t)\mathscr{V}_{t+1}^A + \Big(1-f(x_t)\Big)\mathscr{V}_{t+1}^I\Big]\Big\}$ is the expected value at $t+1$ for an inactive firm when with endogenous probability $f(x_t)$ will be matched with a retailer and gain $\mathscr{V}_{t+1}^A$, and with probability $1-f(x_t)$ will remain inactive and gain $\mathscr{V}_{t+1}^I$ instead. The matching probability $f(x_t)$ is a function of the intermediate goods market tightness x_t defined as the relative number of open searchers relative to the number of inactive intermediate goods firms $x_t \equiv S_t/I_t$.

The surplus of an active intermediate goods firm from an existing match is thus given by

$$S_t^m \equiv \mathscr{V}_t^A - \mathscr{V}_t^I$$

After replacing the expressions of $\mathscr{V}_t^A$ from (2) and of $\mathscr{V}_t^I$ from (3), and using intermediate goods firms' production technology (1) , we can write the surplus S_t^m as a function of y_t^m, p_t^m and k_t^m :

$$S_t^m(p_t^m, y_t^m, k_t^m) = (1-\tau^*)\frac{p_t^m}{P_t}y_t^m - \frac{W_t}{P_t}l_t^m(y_t^m, k_t^m) - \frac{Q_t^k}{P_t}k_t^m + E_t\Big\{\Lambda_{t,t+1}\Big[\frac{Q_{t+1}^k}{P_{t+1}}k_t^m\Big]\Big\} + \\ + \chi_m + (1-\delta-f(x_t))E_t\{\Lambda_{t,t+1}[S_{t+1}^m(p_{t+1}^m, y_{t+1}^m, k_{t+1}^m)]\} \tag{4}$$

The production of intermediate goods is subject to credit frictions. A firm producing at time t needs to finance the wage bill in advance of sales. The firm starts with no net worth and distributes profits each period to the household. It thus needs to finance the wage bill with an intra-temporal loan. There are two sources of credit available: secured bank credit and big tech credit.

Bank credit $\mathscr{L}_t^s$ is limited by the expected resale value of firms' collateral,

$$\mathscr{L}_t^s \leq \nu_t E_t\Big\{\Lambda_{t,t+1}\Big[\frac{Q_{t+1}^k}{P_{t+1}}k_t^m\Big]\Big\} \tag{5}$$

ν_t is the share of the capital value that can be realised by selling it in period $t+1$ and evolves according to the process $log(\nu_t) = \rho_\nu log(\nu_{t-1}) + \epsilon_t^\nu$, with $\rho_\nu \in [0,1]$. Variations in ν_t act as exogenous shocks to the availability of bank credit, possibly capturing bank balance sheet considerations that we do not model here.

The amount of credit that the big tech firm is willing to extend to intermediate goods firms is also limited by moral hazard. The limit equals the expected gains for intermediate goods firms from retaining access to the big tech network in the future ($\widetilde{\mathscr{V}}_{t+1}$),

$$\mathscr{L}_t^b \leq b\widetilde{\mathscr{V}}_{t+1}$$

This is because intermediate goods firms which default on big tech credit are automatically excluded from the e-commerce platform in the following period. If credit exceeded the expected gain of remaining on the platform, firms would be better off defaulting. Anticipating this, the big tech creditor does not extend credit above what firm borrowers would get if they absconded such that the latter always have an incentive to repay. We assume that only a share $b \in [0,1)$ can be pledged as network collateral. This accounts for alternative retail options that intermediate goods firms can use to sell products other than the big tech e-commerce platform.[11] We further assume that firms

[11] If firms had the alternative to sell products outside the e-commerce platform, and chose to default, they would lose the *difference* between the expected profits on the big tech platform and those earned with the alternative retail option, net of switching costs to those alternative options. To the extent that this difference is (roughly) proportional

are excluded from the platform for a finite number of periods to reflect the incentive of the big tech not to exclude firms forever because of the associated loss of fees. Denoting by κ the number of exclusion periods, we obtain

$$\tilde{\mathscr{V}}_{t+1} = \mathscr{V}_{t+1} - E_t\Big\{\Lambda_{t,t+\kappa}\Big[\mathscr{V}_{t+\kappa+1}\Big]\Big\} \tag{6}$$

where $\mathscr{V}_{t+\kappa+1} \equiv E_t\Big\{\Lambda_{t+\kappa,t+\kappa+1}\Big[(1-\delta)\mathscr{V}^A_{t+\kappa+1} + \delta\mathscr{V}^I_{t+\kappa+1}\Big]\Big\}$ is the expected value at time $t+\kappa$ of regaining access to the platform from $t+\kappa+1$ onward, and $\Lambda_{t,t+\kappa} \equiv \beta^\kappa \frac{C^{-\sigma}_{t+\kappa}}{C^{-\sigma}_t}$ is the stochastic real discount factor at time t of consumption units at time $t+\kappa$.

Given the two credit constraints, the total amount of credit that intermediate goods firms can get is limited by both collateral and incentives to remain in the big tech network, namely

$$\frac{W_t}{P_t} l^m_t = \mathscr{L}^b_t + \mathscr{L}^s_t \leq b\tilde{\mathscr{V}}_{t+1} + \nu_t E_t\Big\{\Lambda_{t,t+1}\Big[\frac{Q^k_{t+1}}{P_{t+1}} k^m_t\Big]\Big\}$$

3.1.3 Retailers

There is a continuum of size one of such firms. They are all identical and perfectly competitive. A typical retailer buys intermediate goods from all A_t intermediate goods firms active at time t via the big tech commerce platform, and produces final goods Y_t with the linear technology $Y_t = \int_0^{A_t} y^m_t(i)di$, where $y^m_t(i)$ is the quantity purchased from the active intermediate goods firm $i \in [0, A_t]$. Retailers purchase the same quantity from each active intermediate goods firm i so that $y^m_t(i) = y^m_t, \ \forall i \in [0, A_t]$, implying that the output of the final goods sector equals $Y_t = A_t y^m_t$.

Each period a typical retailer actively searches on the big tech commerce platform for S_t intermediate goods suppliers for use in the following period. The value of a search $\mathcal{I}^s_t$ (the subscript s denoting "search") equals

$$\mathcal{I}^s_t \equiv -\chi_r + g(x_t)E_t\{\Lambda_{t,t+1}\mathcal{I}^B_{t+1}\} \tag{7}$$

where $g(x_t)E_t\{\Lambda_{t,t+1}\mathcal{I}^B_{t+1}\}$ is the expected gain of finding an intermediate goods supplier. Here, $g(x_t)$ denotes the probability to find a supplier (to be defined shortly), and $\mathcal{I}^B_{t+1}$ the state–contingent value at $t+1$ of being matched with a supplier (where B stands for "business" relation). As long as the value of a search $\mathcal{I}^s_t$ is strictly positive, retailers will add new searches. As the number of searches increases, the probability $g(x_t)$ that any open search gets matched with a suitable intermediate

to the expected profits on the e-commerce platform, setting $b < 1$ accounts for this dimension.

goods supplier decreases. A lower probability of filling an open search reduces the attractiveness of looking for an additional supplier, and decreases the value of an open search. Thus, at each date t, retailers will look for new suppliers until the marginal value of an open search is zero. Thus, the number of searches S_t is obtained for $\mathcal{I}_t^s = 0$, namely for $\chi_r = g(x_t)E_t\{\Lambda_{t,t+1}\mathcal{I}_{t+1}^B\}$. The value of an existing relation with an intermediate goods supplier at time t equals

$$\mathcal{I}_t^B = y_t^m - \frac{p_t^m}{P_t} y_t^m + (1-\delta)E_t\Big\{\Lambda_{t,t+1}\mathcal{I}_{t+1}^B\Big\} \tag{8}$$

where $y_t^m - \frac{p_t^m}{P_t} y_t^m$ are current real profits for the retailer from the relation with a supplier, and $(1-\delta)E_t\{\Lambda_{t,t+1}\mathcal{I}_{t+1}^B\}$ is the expected value of the match at $t+1$ when with probability $1-\delta$ it will be maintained.

The surplus of a typical retailer from an existing match is thus given by $S_t^r \equiv \mathcal{I}_t^B - \mathcal{I}_t^s$, which can be written in equilibrium as

$$S_t^r(p_t^m, y_t^m) \equiv y_t^m - \frac{p_t^m}{P_t} y_t^m + \frac{\chi_r(1-\delta)}{g(x_t)}. \tag{9}$$

3.1.4 Matching

Retailers search each period for inactive intermediate goods firms on the e-commerce platform. If a match is formed at time t, intermediate goods firms start producing and selling inputs to retailers at time $t+1$. The matching function

$$M(S_t, I_t) = \sigma_m S_t^{\eta} I_t^{1-\eta}, \eta \in (0,1) \tag{10}$$

gives the number of inactive intermediate goods firms which post advertisements (and do not produce) closing a deal with the retail sector at time t. σ_m is the scale parameter reflecting the efficiency of the matching process. The parameter captures the ability of the big tech to collect data and process information about firms' characteristics. The higher the volume of available data, the more efficiently the big tech firm can match sellers with buyers on the e-commerce platform. The number of intermediate goods firms active at time $t+1$ (determined at t) evolves according to the following dynamic equation

$$A_{t+1} = (1-\delta)A_t + M(S_t, I_t),$$

which simply says that the number of matched (active) intermediate goods firms at the beginning of period $t+1$, A_{t+1}, is given by the fraction of matches in t that survives to the next period, $(1-\delta)A_t$, plus the newly-formed matches at time t, $M(S_t, I_t)$.

The probability that an open search is filled with an inactive intermediate goods firm, $g(x_t)$, decreases in x_t, and equals

$$g(x_t) \equiv \frac{M(S_t, I_t)}{S_t} = \sigma_m \Big(\frac{S_t}{I_t}\Big)^{\eta-1} = \sigma_m x_t^{\eta-1} \tag{11}$$

Similarly, the probability that any inactive intermediate goods firm is matched with an open search at time t, $f(x_t)$, increases in x_t, and is given by

$$f(x_t) \equiv \frac{M(S_t, I_t)}{I_t} = \sigma_m \Big(\frac{S_t}{I_t}\Big)^{\eta} = \sigma_m x_t^{\eta}. \tag{12}$$

3.2 Bargaining

In equilibrium, the retailers and the intermediate goods firms which are in a match obtain a total return that is strictly higher than the expected return of unmatched retailers and intermediate goods firms. The reason is that if the two firms separate, each will have to go through an expensive and time-consuming process of search before meeting another partner. Hence, a realized match needs to share this pure economic rent equal to the sum of expected search costs for the two parties.

We assume that this rent is shared through period–by–period collective Nash bargaining between each retailer and its suppliers. Bargaining takes place along two dimensions, the price p_t^m of an intermediate good and the output y_t^m of an intermediate goods firm, and it is subject to the technology and credit constraints of intermediate goods firms. Since all retailers are identical, active intermediate good firms will sell the same quantity y_t^m at the same price p_t^m to all its customer retailers. The optimal choices of p_t^m and y_t^m implicitly require an appropriate choice of the capital stock k_t^m. The set $\{p_t^m, y_t^m, k_t^m\}$ is given by the solution to the following bargaining problem:

$$\{p_t^m, y_t^m, k_t^m\} = argmax\Big[S_t^m(p_t^m, y_t^m, k_t^m)\Big]^{\epsilon}\Big[S_t^r(p_t^m, y_t^m)\Big]^{1-\epsilon}, \quad 0 < \epsilon < 1$$

subject to

$$\frac{W_t}{P_t} l_t^m(y_t^m, k_t^m) \leq b\widetilde{\mathscr{V}}_{t+1} + \nu E_t\Big\{\Lambda_{t,t+1}\Big[\frac{Q_{t+1}^k}{P_{t+1}} k_t^m\Big]\Big\} \tag{13}$$

where ϵ is the (relative) bargaining power of the active intermediate goods firms.

3.2.1 Central bank

The central bank sets the nominal risk–free policy rate i_t in line with the simple Taylor-type rule

$$1 + i_t = \frac{1}{\beta} (1 + i_{t-1})^{\phi_i} \left[\Pi_t^{\phi_\pi} \left(\frac{Y_t}{Y} \right)^{\phi_y} \right]^{(1-\phi_i)} e^{\mu_t} \tag{14}$$

where Y is steady-state output and μ_t is a monetary policy shock following an AR(1) process $\mu_t = \rho_\mu \mu_{t-1} + \epsilon_t^\mu$, where $\rho_\mu \in [0, 1)$.

3.3 Empirical evidence and calibration

We parameterize our model at quarterly frequency using data for the US economy. In particular, our model capture the negligible amount of credit extended by big tech in the US (USD 6.7 bn in 2020). In our numerical analysis, we use this calibrated version of the model to proxy the economy where the only source of finance is bank credit. We then compare this benchmark economy to one where the big tech's matching efficiency and/or the share of big tech credit is increased.

In our model, the impact of big tech lending on the responses of credit and real activity to business cycle fluctuations crucially depends on the strength of the network channel relative to the physical collateral channel. We discipline the model in two steps. First, we documents the estimated reaction of commercial property prices and e-commerce activity to monetary policy based on US data.[12] Second, we calibrate the model to replicate this empirical evidence.

We estimate the dynamic responses of log-transformed real e-commerce sales and log-transformed real commercial property prices to monetary policy using Jordà (2005)'s local projection method. That is, for each forecast horizon $h = 0, .., H - 1$ we run a distinct regression for a given dependent variable y (either the log-transformed real commerce sales, or the log-transformed real commercial property prices) on a high-frequency identified monetary policy surprise (mps_t) and a vector of

[12] Ideally, one would like to estimate the direct impact of monetary policy on vendors' profits. However, long enough series for such variables are not yet publicly available.

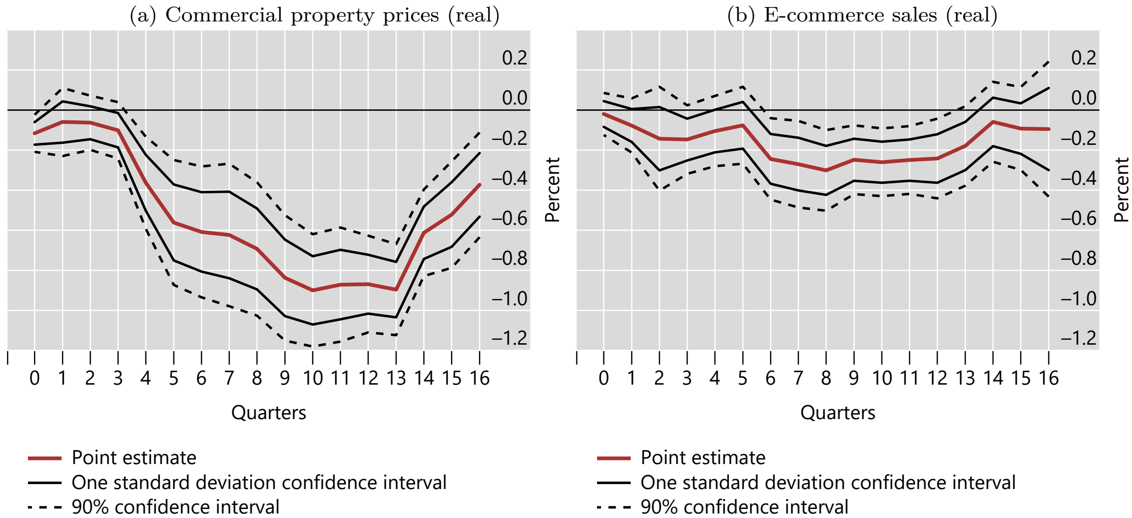

Figure 7: Estimated dynamic responses to an unexpected monetary policy tightening

Notes: Shown are the coefficients β_h in the local projection regression (15) for $h = 0, ..., 16$. The unexpected monetary tightening is an unexpected 25 basis points rise in the policy rate.

control variables $\mathbf{x}_t$:[13]

$$y_{t+h} = \alpha_h + \beta_h \cdot mps_t + \mathbf{A_h} \cdot \mathbf{x}_t + e_{t+h}, \tag{15}$$

where the forward term y_{t+h} captures the value of the dependent variable h periods after the monetary policy shock, the coefficient β_h gives the response of the dependant variable at time $t+h$ to a shock at time t, $\mathbf{A_h}$ is the coefficient matrix of control variables at horizon h (to be described shortly), and e_{t+h} is the regression residual at horizon h. We report Newey-West standard errors to account for serial correlation. Following Ramey (2016), we include in the vector of control variables $\mathbf{x}_t$ lags of the dependant variable, lags of the monetary policy surprise, contemporaneous and lagged values of the log-transformed CPI, of the unemployment rate, of the log-transformed industrial production, the Wu-Xia shadow federal funds rate, and further add to this list the Gilchrist and Zakrajšek (2012) equity finance premium as suggested by Caldara and Herbst (2019). The number of lags is chosen optimally according to the SBIC information criteria and equals one. Our estimation period runs from 1999:Q4-2016:Q2 because the series of e-commerce sales series begins in 1999:Q4

[13]Commercial property prices are the commercial real estate prices for the United States available in the FRED database of the Federal Reserve Bank of St. Louis. E-commerce sales are the retail sales (total excluding food services, current prices) for the United States from the U.S. Census Bureau Data. Both series are quarterly, seasonally adjusted and deflated using the 2010 CPI. We use the high frequency identified monetary policy surprises derived by Jarociński and Karadi (2020). These surprises are constructed from surprises in the 3-month fed funds futures to measure changes in expectations about short term interest rates around Federal Open Market Committee (FOMC) announcements, and are corrected for "information channel" biases using sign restrictions. The high frequency monetary policy surprises are converted to quarterly series by summing observations within each quarter.

and that of high-frequency monetary policy surprises ends in 2016:Q2. Figure 7 reports the dynamic responses of real commercial property prices (left panel) and e-commerce sales (right panel) to a monetary policy shock in the US. The estimates show higher responsiveness on impact of commercial property prices relative to e-commerce sales.

Our calibration strategy is described in details in appendix B and targeted at replicating the evidence on the reaction of e-commerce sales and property prices to a monetary policy shock.

4 Numerical results

This section provides a model-based evaluation of the impact of big tech's financial intermediation services on economic activity, the transmission of monetary policy, and the propagation of adverse financial shocks.

4.1 Big tech and the macroeconomy

We first analyse how the availability of big tech credit affects the long run (steady-state) allocation, and how the impact changes with the matching efficiency of the big tech e-commerce platform.

At the core of our results is a feedback between the volume of big tech credit and the value of operating on the platform for intermediate goods firms. The availability of big tech credit enables firms to expand output and trade, which increases the value for intermediate goods firms of being active in the network. Thus, at a given matching efficiency, expected profits and network collateral are higher in the presence of big tech credit and so is the opportunity cost of defaulting on this type of credit. This in turn reduces the tighteness of the big tech credit constraint and further expands production, in a positive feedback loop.

To analyse the macroeconomic impact of an expansion of big tech into financial activities, we solve the steady-state of the model as a function of the matching efficiency σ_m. For simplicity, we assume a steady-state with zero inflation and zero growth. Our main findings are reported in Figure 8, which compares steady state outcomes with both types of credit (blue line) and with bank credit only (baseline, red line).[14] For a given matching efficiency σ_m, the availability of big tech credit expands total credit and relaxes credit constraints (middle right panel) relative to an economy with

[14]The baseline economy with bank credit only (red line) is one where $b = 0$, ie firm profits cannot be pledged, while the economy where both bank credit and big tech credit are available (blue line) is one where $b = 0.3$.

bank credit only. The expansion in credit supply boosts aggregate output approaching it to the efficient level (top left panel). These effects work via the binding borrowing constraint. Specifically, the availability of big tech credit allows intermediate goods firms to additionally pledge a share of their future expected profits $\tilde{\mathscr{V}}_{t+1}$ as network collateral (top right panel) alongside physical capital. The higher collateral allows these firms to increase their borrowing and hire more labor. This relaxes the credit constraints and leads to higher aggregate output.

The higher the matching efficiency σ_m, the stronger the effect of big tech credit on the steady-state allocation. This is reflected in the larger differences between the blue and red lines for higher values of σ_m. A higher matching efficiency increases the probability for an intermediate goods firm to find a client $f(x)$ both directly by making a match more likely and indirectly by raising the intermediate goods market tightness x. The rise in intermediate goods market tightness is due to the decline in the number of inactive intermediate goods firms I, as more of these firms become active on the platform. The higher probability to find a client (bottom left panel) boosts the expected profits of intermediate goods firms in inactive and active contingencies and translates in higher network collateral $\tilde{\mathscr{V}}$. The higher network collateral allows intermediate goods firms to borrow more and hire more labor, relaxing by more the borrowing constraints relative to the case with bank credit only and boosting total credit and output by more. Provided firms can pledge a high enough share of their expected profits on the platform (30% in the figure), the increase in matching efficiency can reduce the tightness of credit constraints λ up to the point where the economy enters its credit–frictionless region ($\lambda \to 0$ as σ_m increases, middle right panel).

Notably, the efficiency gains associated to the use of the big tech platform are limited by the distortionary nature of their fees. Variable fees distort the allocation via the firm level of output (a pure sales tax effect), without affecting the matching process (i.e. the equilibrium level of active sellers). The higher the fees levied in proportion to sales on the big tech platform τ^*, the larger the ”sales-tax” distortions (see equation (29)), and the lower the net efficiency gains.

The steady state analysis can also shed light on the impact of the increase of big tech credit on bank lending activity. As matching efficiency improves, the share of big tech credit in total credit steadily increases. Notably, the increase in the share of big tech credit is further reinforced by a decline in the supply of bank credit. This latter is due to the loosening of credit constraints which makes physical capital less valuable as collateral, and consequently, reduces its price. As a result, as

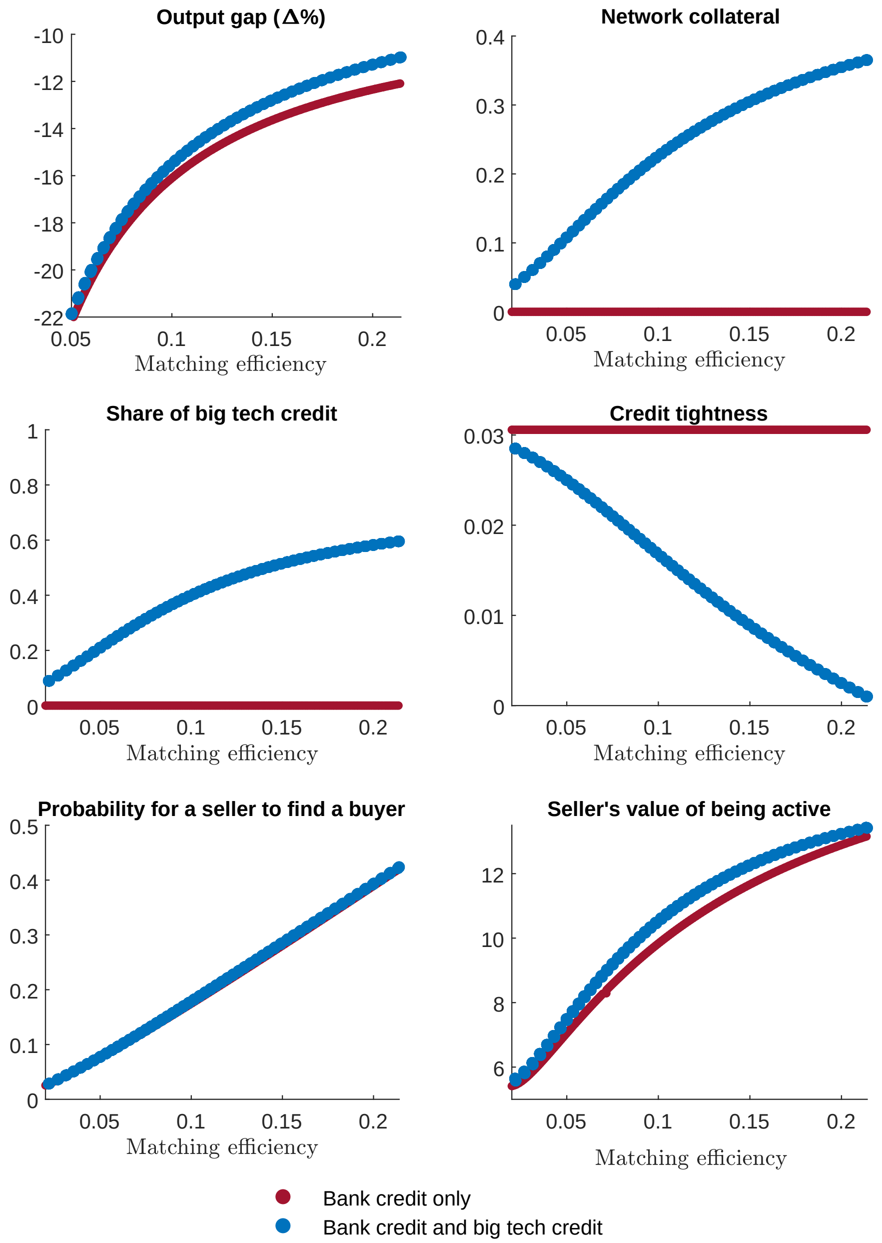

Figure 8: Steady-state equilibrium and matching efficiency on the e-commerce platform

Notes: Output gap: percentage deviation of output Y from its efficient level. Network collateral: expected profits that vendors on the platform would lose in case of default $b(1-\beta^k)\mathscr{V}$. Credit tightness: λ. Probability for a vendor to find a client: $f(x)$. Vendors' value of being active: $\mathscr{V}^a$. $\nu = 0.1$.

matching efficiency on the e-commerce platform improves, the rise in big tech credit slightly crowds out bank credit, and the two types of credit become strategic substitutes in equilibrium.

4.2 Big tech credit and the transmission of monetary policy

We analyse here how the availability of big tech credit affects the transmission of monetary policy and how it interacts with banks' lending activity.

Figure 9 compares the responses to a 25 basis points monetary policy tightening shock in the economy with both big tech and bank credit (blue line) to those in an economy with bank credit only (red line).[15] In the economy we consider, which features a relatively low level of matching efficiency, big tech credit responds less than bank credit because profits on the platform ("network value") react less than real estate prices. As a result, total credit and output react less than in the baseline case with bank credit only, implying that big tech credit mitigates the impact of the tightening shock.

The availability of big tech credit dampens the effect of the shock on output not only because it reacts less than bank credit, but also because it mitigates the reaction of bank credit. Specifically, bank credit responds less in the economy with both big tech and bank credit than in the baseline economy with bank credit only. This is because big tech's additional supply of credit loosens credit constraints, thereby weakening the financial accelerator.

Notably, the mitigation observed in the responses of credit and output to a monetary policy shock varies non-linearly with the big tech's efficiency parameter σ_m. The reason is that the transmission of the shock depends crucially on two factors: the gap between the responses of network collateral and physical collateral and the share of big tech credit, which are both affected by the matching efficiency between sellers and buyers on the e-commerce platform. Consequently, the overall impact of big tech credit on the transmission of monetary policy varies with this structural parameter.

Table 5 summarizes the results in the particular case of a 25 basis points tightening monetary policy shock. Columns two to five show the responses on impact of big tech credit, bank credit, total credit and output to the shock for different levels of the matching efficiency σ_m in the economy where firms have access to both types of credit. Columns six and seven further show the corresponding responses in the baseline economy with bank credit only. When matching efficiency is relatively low (first row), the drop in big tech credit is lower (0.68 percent) than the drop in bank credit (1.41 percent). As a result, provided the share of big tech credit is high enough, the supply of credit by

[15]The share of big tech credit in total credit in our counterfactual economy reaches 40%

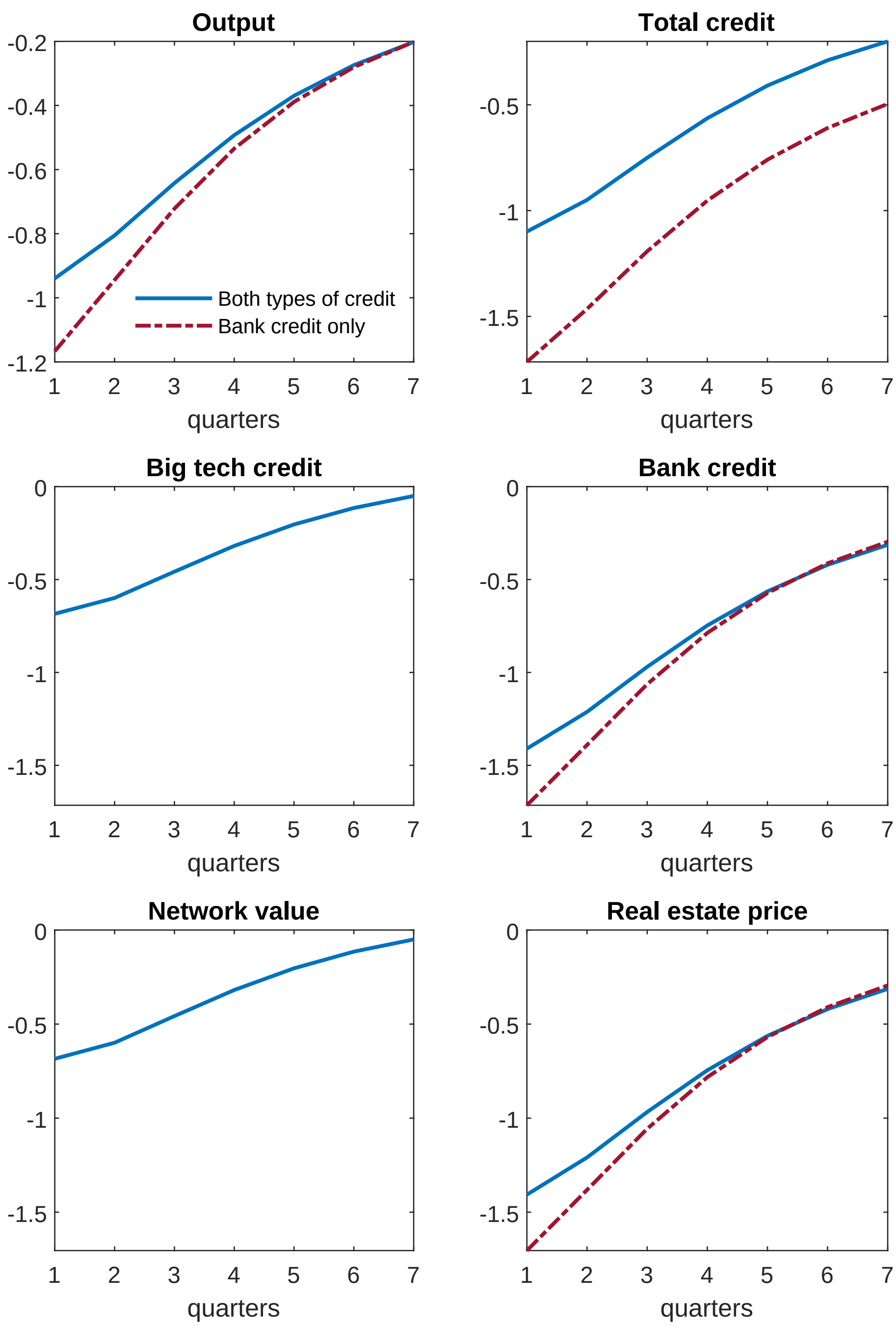

Figure 9: Dynamic responses to a monetary policy shock

Notes: The monetary policy shock is due to a monetary surprise ϵ_t^{ν} of 25 basis points. Low matching efficiency $\sigma_m = 0.01$. Y-axis: percentage deviation from steady-state.

big techs works to dampen the response of total credit to a tightening shock. In particular, total credit drops by 1.09 percent in the economy with both types of credit instead of 1.71 percent in the baseline economy with bank credit only. With total credit reacting less, the response of output is also mitigated in the presence of big tech credit relatively to the case with bank credit only – it drops by 0.93 percent instead of 1.16 percent.

As the matching efficiency on the e-commerce platform rises (second row), big tech credit starts reacting more to the shock in the counterfactual economy, but still less than bank credit. This is explained by a higher sensitivity of network collateral to the shock. With less matching frictions, the average probability for a firm to become active once inactive $f(x)$ is higher, implying that network collateral $\mathscr{V}_t$ becomes more closely tied to the value of being active $\mathscr{V}_t^a$, and hence to period profits and capital return earned on the platform. These latter are sensitive to the business cycle as opposed to net losses while inactive, which equal fixed fees and hence are not sensitive to shocks. The enhanced sensitivity of big tech credit reduces the gaps between the reactions in the counterfactual economy and those in the case with bank credit only. Credit (output) now falls by 1.31 percent (1.01 percent) in the former economy, compared to 1.71 percent (1.16 percent) in the latter, showing that the mitigation effect of big tech credit on the propagation of the monetary policy shock weakens as the matching efficiency rises.

	Baseline model with both types of credit				Bank credit only	
Matching efficiency/Variables	Big tech credit	Bank credit	Total credit	Output	Credit	Output
Low	-0.68	-1.41	-1.09	-0.93	-1.71	-1.16
Intermediate	-1.31	-1.49	-1.31	-1.01	-1.71	-1.16
High	-0.84	-0.84	-0.84	-0.84	-1.71	-1.16

Table 5: Matching efficiency and the effect of monetary policy shocks on credit and output

Notes: Effect on impact to a positive 25 basis points monetary policy surprise. Matching efficiency levels: $\sigma_m \in \{0.01, 0.04\}$

Eventually, once the matching efficiency becomes sufficiently high to push the economy beyond its credit frictionless limit, the financial accelerator vanishes. The reactions of credit and output to the monetary policy shock drop sharply. Credit (output) now falls by 0.84 percent (0.84 percent) in the economy with both bank credit and big tech credit, compared to 1.71 percent (1.16 percent) in the baseline economy. This represents a large mitigation effect relative to the economy with bank credit only, where the financial friction remains binding.

The response we obtain in reaction to a monetary policy shock arises more generally in reaction to demand shocks and technology shocks. In particular, dynamic responses of output and credit to a demand preference shock ϵ_t^z of -0.5 percentage points are identical to those to a 25 basis points monetary policy shock.

4.3 Big tech credit and financial stability

We next turn to evaluate the role of big tech credit for financial stability. In particular, we ask whether the availability of big tech credit can shield the economy from the impact of an adverse financial shock.

We consider the response of the economy to a surprise decline in ν_t, which affects the resale value of firms' capital and its pledgeability at banks. Figure 10 compares the responses to the shock in the economy with both big tech and bank capital (blue line) to those in the baseline economy with bank credit only (red line).

When bank credit is the only source of financing for firms, the shock to ν_t reduces the collateral value of capital. As a consequence, the supply of bank (and total) credit contracts, tightening the credit constraints and strengthening the financial accelerator. This is also true in the economy with both types of credit. The shock to the resale value of capital reduces its price and, everything else equal, lowers the supply of bank credit. In this economy, however, the reduction in the price of capital also boosts the profits of intermediate firms and their network value, increasing the supply of big tech credit. The overall impact is only a mild decline in total credit and a mild increase in the tightness of the credit constraints. The higher current and future profits of intermediate goods firms help sustain the demand for capital and limit the fall in its price. As a result of these general equilibrium effects, the contraction of bank credit is more contained than in the baseline economy.

Overall, the availability of big tech credit contributes to ensure financial stability along two dimensions. On the one hand, it reduces the negative impact of the adverse financial shock on bank lending. On the other hand, it acts as a 'spare tyre' for the economy, preventing a larger contraction of total credit and real activity.

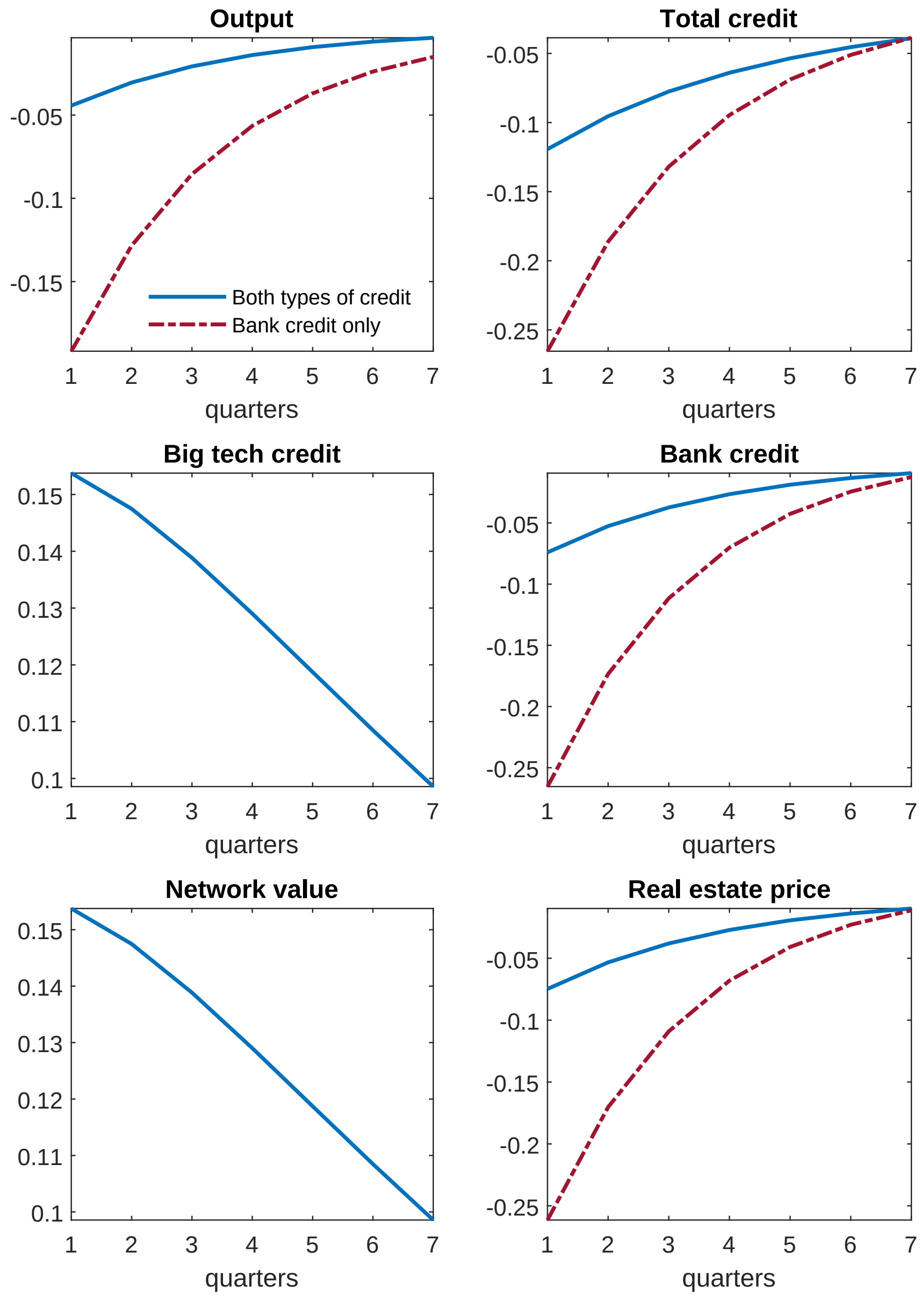

Figure 10: Dynamic responses to an adverse financial shock

Notes: The financial shock is surprise innovation ϵ_t^{ν} of 25 basis points to the pledgeable share of the capital value. Low matching efficiency: $\sigma_m = 0.01$. Y-axis: percentage deviation from steady-state.

5 Conclusions

Big tech credit is becoming an increasingly important source of non-bank funding. Motivated by this rapidly evolving financial landscape, this paper documents the role played by big tech companies and evaluates the challenges they pose to central banks. In particular, our model-based analysis sheds light on the implications of big tech's entry into finance for the macroeconomy, the transmission of monetary policy, and financial stability, highlighting three main messages.

First, an expansion in big techs' activities can increase the value for firms of trading on the platform and the availability of big tech credit. This helps relax financing constraints and raise firms' output, although the efficiency gains of big tech credit provision are limited by the distortionary nature of the fees collected from platform users.

Second, the transmission of monetary policy depends crucially on the difference between the responses of network collateral and physical collateral, and on the share of big tech credit, both of which depend on the efficiency of big tech in facilitating trading on its platform. When the efficiency is low, big tech credit reacts less than bank credit to monetary policy shocks. However, as the matching efficiency rises, network collateral becomes more sensitive and the mitigating effect of big tech credit weakens. Our analysis therefore suggests that the sensitivity of the different sources of finance to monetary policy shocks - and more broadly to aggregate shocks - will differ across countries, depending on their financial development and efficiency of the e-commerce platforms.

Third, the availability of big tech credit helps mitigate the impact of shocks on the price of capital and its collateral value. By doing so, it reduces the negative effects of financial shocks that decrease bank credit, providing a 'spare tyre' for the economy, and preventing a larger contraction of total credit and real activity.

While our stylized model focuses on the effects of the big tech business model on financial intermediation, it is not suitable for evaluating other relevant risks. On one hand, big tech's activity could improve financial inclusion and serve as an alternative to bank credit; on the other, it introduces new risks related to market competition and data privacy. Moreover, the supply of certain big tech services - such as payment, asset management, data analysis and cloud computing - is highly concentrated, which could create single points of failure and increase overall systemic risks. We leave the quantification of these risks and the analysis of optimal regulation to future research.

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A Model

We describe here the problem of the households, the government and the central bank. We also provide first-order conditions for the problem of the firms, and market clearing conditions.

A.1 Households

The economy is populated by a large number of identical infinitely-lived households. Each household is made up of a continuum of members, each specialized in a different labor service indexed by $j \in [0,1]$. Income is pooled within each household. A typical household chooses each period how much to consume C_t and how much to invest in nominal risk–free public bonds B_t and equity $\mathscr{E}_t$ to maximize intertemporal utility,

$$E_0\left\{\sum_{t=0}^{\infty} Z_t\beta^t\left(\frac{C_t^{1-\sigma}-1}{1-\sigma}-\chi\int_0^1\frac{L_t(j)^{1+\varphi}}{1+\varphi}dj\right)\right\}$$

subject to the sequence of budget constraints

$$P_tC_t+B_t^h+\mathscr{E}_tQ_t^e\leq\int_0^1 W_t(j)L_t(j)dj+B_{t-1}^h(1+i_{t-1})+\mathscr{E}_tD_t^e+\mathscr{E}_{t-1}Q_t^e+\Upsilon_t \tag{16}$$

for $t=0,1,2...$, taking employment choices $L_t(j)$ and labor income $\int_0^1 W_t(j)L_t(j)dj$ as given. Individually, each household has no influence on nominal wage rates $W_t(j)$ set by unions, or employment levels $L_t(j)$ determined by firms. P_t is the price of a final consumption good, Q_t^e is the unit price of equity, i_t is the nominal interest rate on public bonds bought at t, D_t^e is the dividend paid on equity, $\Upsilon_t \equiv \Upsilon_t^g+\Upsilon_t^p+\Upsilon_t^b$ are aggregate (net) lump-sum transfers received by the households, where Υ_t^g are lump-sum net transfers by the government, Υ_t^p are lump-sum net pay–outs by the private sector (i.e. by intermediate goods firms and retailers) and Υ_t^b are lump-sum net transfers by the big tech firm. Z_t is a demand preference shock which follows the exogenous process $log(Z_t)=\rho_z log(Z_{t-1})+\varepsilon_t^z$, with $\rho_z\in[0,1)$. The household receives the wages for all types of labor services in the form of bank deposits at the beginning of period t and uses them within the period to buy final goods. The maximization problem is subject to standard solvency constraints ruling out Ponzi schemes on bonds and equity

$$\lim_{T\to\infty}E_0\left\{\Lambda_{0,T}\frac{B_T^h}{P_T}\right\}\geq 0,\qquad \lim_{T\to\infty}E_0\left\{\Lambda_{0,T}\frac{\mathscr{E}_TQ_T^e}{P_T}\right\}\geq 0, \tag{17}$$

where $\Lambda_{0,T} \equiv \beta^T \frac{C_T^{-\sigma}}{C_t^{-\sigma}} \frac{Z_T}{Z_t}$. Households' optimality conditions are given by

$$1 = E_t \Big\{ \Lambda_{t,t+1} \Pi_{t+1}^{-1} (1 + i_t) \Big\}, \tag{18}$$

$$Q_t^e = D_t^e + E_t \Big\{ \Lambda_{t,t+1} \Pi_{t+1}^{-1} Q_{t+1}^e \Big\}, \tag{19}$$

together with the sequence of budget constraints (16) for $t = 0, 1, 2, ...,$ and the transversality conditions (17), where $\Lambda_{t,t+1} \equiv \beta \frac{C_{t+1}^{-\sigma}}{C_t^{-\sigma}} \frac{Z_{t+1}}{Z_t}$ is the real stochastic discount factor, and $\Pi_t \equiv \frac{P_t}{P_{t-1}}$ is the (gross) inflation rate between $t-1$ and t.

Each period workers specialized in a given type of labor can reset their nominal wage only with probability $1 - \theta_w$. Wage dynamics are described up to a first-order log-linear approximation by

$$\pi_t^w = \beta E_t \{ \pi_{t+1}^w \} - \lambda_w \widehat{\mu_t}^w \tag{20}$$

where $\pi_t^w \equiv log(W_t) - log(W_{t-1})$ is the wage inflation rate, $\lambda_w \equiv \frac{(1-\theta_w)(1-\beta\theta_w)}{\theta_w(1+\epsilon_w\varphi)}$, with ϵ_w the elasticity of substitution among labor types indexed by j, and $\widehat{\mu_t}^w \equiv \mu_t^w - \mu^w$ denotes the deviations of the economy's (log) average wage markup $\mu_t^w \equiv (w_t - p_t) - (log(\chi) + \sigma c_t + \varphi l_t)$ from its steady-state level μ^w.

A.2 Banks

Banks finance intra-period secured loans by issuing intra-period deposits. These deposits are received by households at the beginning of the period and used to buy final goods by the end of the period.

A.3 Government

The government issues the one period public nominal risk–free bonds held by households B_t^h and by the big tech firm B_t^b, and balances the budget with lump–sum (net) transfers Υ_t^g:

$$B_t^h + B_t^b = \Big(B_{t-1}^h + B_{t-1}^b \Big) \Big(1 + i_{t-1} \Big) + \Upsilon_t^g \tag{21}$$

A.4 Market clearing

Final goods market: Market clearing requires aggregate demand for final goods by households to equal their aggregate supply by retailers:

$$C_t = Y_t \tag{22}$$

Intermediate goods market: Market clearing requires aggregate demand for intermediate goods by retailers to equal aggregate supply by all active intermediate goods firms at time t:

$$Y_t = A_t y_t^m \tag{23}$$

Capital market: Capital ("real estate") is in fixed aggregate supply $\bar{K}$ and does not depreciate. Market clearing requires aggregate demand for capital by all active intermediate goods firms to equal its aggregate supply:

$$A_t k_t^m = \bar{K} \tag{24}$$

Labor market: Market clearing requires aggregate demand for all labor types by all active intermediate goods firms to equal its supply by households:

$$\begin{aligned}\int_0^{A_t} \int_0^1 l_t^m(i,j) dj di &= L_t \\ \Delta_{w,t} A_t l_t^m &= L_t\end{aligned} \tag{25}$$

where $\Delta_{w,t} \equiv \int_0^1 \left(\frac{W_t(j)}{W_t}\right)^{-\epsilon_w}$ is equal to 1 up to a first order log-linear approximation.

Bond market: Market clearing requires that demand for public bonds by the household and by the big tech firm to equal their supply by the government:

$$B_t^h + B_t^b = B_t \tag{26}$$

Equity market: Market clearing requires that the demand for equity claims by households to equal their supply by active intermediate goods firms wiling to finance physical capital:

$$\mathscr{E}_t = A_t k_t^m \tag{27}$$

A.5 Bargaining

In equilibrium, the price p_t^m chosen by the match satisfies the optimality condition

$$\epsilon\,(1-\tau^*)S_t^r = (1-\epsilon)S_t^m \tag{28}$$

where both surpluses S_t^m and S_t^r are a function of p_t^m, y_t^m and k_t^m.

The optimality condition with respect to y_t^m writes

$$y_t^m:\ \epsilon S_t^r\left(\frac{W_t}{P_t}\frac{\partial l_t^m(y_t^m,k_t^m)}{\partial y_t^m}-(1-\tau^*)\frac{p_t^m}{P_t}\right)=(1-\epsilon)S_t^m\left(1-\frac{p_t^m}{P_t}-\frac{\lambda_t}{1-\epsilon}\frac{W_t}{P_t}\frac{\partial l_t^m(y_t^m,k_t^m)}{\partial y_t^m}\left(\frac{S_t^r}{S_t^m}\right)^{\epsilon}\right)$$

where $\lambda_t \geq 0$ is the Lagrangian multiplier on a intermediate goods firm's credit constraint. Using (28), this optimality condition can be simplified under our baseline calibration with $\epsilon = 1-\epsilon$ as:[16]

$$1=\frac{1}{1-\alpha}\frac{W_t}{P_t}\frac{l_t^m}{y_t^m}\left[\frac{1}{1-\tau^*}+\frac{\lambda_t}{1-\epsilon}\left(\frac{1}{1-\tau^*}\right)^{\epsilon}\right],\quad \lambda_t\geq 0 \tag{29}$$

The optimality condition with respect to capital for $\epsilon = 1-\epsilon$ writes

$$\frac{Q_t^k}{P_t}=\gamma\frac{y_t^m}{k_t^m}\left[\frac{1+\frac{\lambda_t}{\epsilon}\left(1-\tau^*\right)^{1-\epsilon}}{\frac{1}{1-\tau^*}+\frac{\lambda_t}{1-\epsilon}\left(\frac{1}{1-\tau^*}\right)^{\epsilon}}\right]+\left[1+\frac{\nu\lambda_t}{\epsilon}\left(1-\tau^*\right)^{1-\epsilon}\right]E_t\Big\{\Lambda_{t,t+1}\Big[\frac{Q_{t+1}^k}{P_{t+1}}\Big]\Big\} \tag{30}$$

To sum up, equations (13), (28), (29) and (30) describe the outcome of the bargaining process which determines λ_t, p_t^m, y_t^m, and k_t^m.

B Calibration

It is convenient to split the structural parameters of the model in four groups (Table B1).

The first group includes the standard parameters of the basic NK model. The discount factor β, the curvature of labor disutility φ, the labor share $1-\alpha$, the elasticity of substitution between labor types ε_w, the Calvo index of wage rigidities θ_w and the persistence of shocks are all set to standard textbook values (see Galí (2015)). The labor disutility parameter χ is set to obtain an efficient level of labor equal to one in steady state. The monetary policy coefficients, ϕ_i and ϕ_y are from the Taylor (1993) rule, which we augment with an interest rate smoothing coefficient $\phi_i = 0.8$.

[16] The relative bargaining power of sellers and buyers may play an important role for the equilibrium allocation. In this analysis however we remain agnostic about such effects and give both equal bargaining power $\epsilon = 1-\epsilon = 0.5$.

Table B1: Parametrization

Parameter	Description	Value
β	Discount factor	0.99
σ	Curvature of consumption utility	1.5
φ	Curvature of labor disutility	2
χ	Labor disutility	0.75
$1-\alpha$	Elasticity of output to labor	0.75
ε_w	Elasticity of substitution of labor types	4.5
θ_w	Calvo index of wage rigidities	0.75
ϕ_i	Taylor interest rate smoothing	0.8
ϕ_π	Taylor coefficient inflation	1.5
ϕ_y	Taylor coefficient output	0.5/4
ρ_μ	Persistence monetary policy shock	0.5
ρ_ν	Persistence financial shock	0.9
ρ_z	Persistence demand preference shock	0.5
ρ_a	Persistence technology shock	0.9
ϵ	Relative bargaining power of the seller	0.5
η	Matching function parameter	0.5
δ	Probability to separate from an existing match	5%
$\bar{K}$	Fixed supply of capital (real estate)	1
γ	Elasticity of output to real estate	0.03
ν	Sensitivity working capital to physical collateral	1%
χ_m	Fixed big tech fee for intermediate goods firms	0.05
χ_r	Fixed big tech fee for retailers	0.05
τ^*	Variable big tech fee on intermediate goods sales	8%
b	Share of profits pledgeable as network collateral	$[0; 0.3]$
κ	Exclusion periods from the commerce platform	12
σ_m	Matching efficiency	$[0.01, \infty]$

Note: Values are shown in quarterly rates.

The curvature of consumption utility σ is set larger than one such that property prices respond more than e-commerce sales to monetary policy in the model in line with our empirical findings. The higher $\sigma > 1$, the larger the reaction of the price of capital above that of sales.[17] We choose

[17] This is true with and without big tech credit. Since the average share of big tech credit in the US during the estimation period is negligible, the empirical estimates roughly speak to the dynamics in the absence of big tech credit

$\sigma = 1.5$, which lies in the standard parameter space of basic NK models without credit frictions (e.g. $\sigma = 1$ in Galí (2015) and $\sigma = 2$ in Woodford (2003).[18]

The second group of parameters captures the search and matching frictions. We choose to remain agnostic about the effects of the relative bargaining power ϵ and the relative contribution to matching η by setting both parameters to 0.5.[19] The probability to separate from a match δ is set to 5% which implies an average supplier relation duration of five years consistent with median values within supply chains reported by Cen et al. (2016) based on US Compustat firm level data.[20]

The third group of parameters concerns physical capital. The fixed aggregate supply of capital is normalized to 1 and its index of decreasing returns γ equals 0.03 as in Iacoviello (2005). Conditional on $\sigma > 1$, the capital pledgeability ratio (for working capital credit) ν is a key determinant for how much more the price of capital responds to monetary policy than e-commerce sales when the credit constraint (13) binds: the lower ν, the larger the response of the capital price relatively to that of sales. To match the magnitude of the estimated effects of the monetary shock on sales and property prices in Figure 7, one needs to set ν below the range of empirically plausible values.[21] In doing so however, we face a downward limit: since ν affects the volume of big tech credit in equilibrium, a low value implies a low volume of bank credit in the credit constrained region of the economy, and hence, a very steep rise in the share of big tech credit as matching efficiency increases. Faced with these constraints, we set $\nu = 1\%$.[22]

The forth and final group of parameters concerns the big tech platform. Ideally, one would like to use micro-level evidence to set the values of these parameters. However, aside from variable big tech fees, such evidence is not yet available. We thus set the variable big tech fee τ^* roughly equal to average values in the data (Table 3), choose plausible values for the other variables, and then check the robustness of our findings around these plausible values. In particular, we set the share of vendors' profits pledgeable as network collateral b to 0 in the baseline economy with only bank

(i.e. $b = 0$).

[18] Setting $\sigma > 1$ is also necessary (alongside wage stickiness) for credit frictions to amplify the response of output to monetary policy, and hence for the model to feature a financial accelerator.

[19] These values are standard in the search and matching labor market literature and also simplify the solution of the highly non-linear steady state of the model.

[20] Cen et al. (2016) report a median (mean) supplier relationship duration of 4.9 (5.6) years.

[21] With a working capital credit constraint, one needs a low capital pledgeability ratio to embed a strong financial accelerator in the the basic New Keynesian model with capital in fixed aggregate supply (see Manea (2020)).

[22] Adding the share of physical capital financed with collateralised debt as opposed to equity as an extra parameter in the model would strengthen the financial accelerator at each level of the capital pledgeability ratio ν (see Manea (2020)). This would allow us to replicate the empirical findings in Figure 7 for higher values of ν.

credit and to 30% in the counterfactual economy where big tech credit amounts to 40% of total credit. In both economies, we set the number of exclusion periods from the platform in case of default on big tech credit κ to 12 (that is, three years) and the fixed big tech fees, χ_m and χ_r, to 0.05.[23] Finally, the matching efficiency on the e-commerce platform σ_m is set initially to a low value (0.01) and is then varied to see how its increase affects the long run allocation and the transmission of aggregate shocks.

[23] Setting instead the exclusion period to two, four or five years, or the share of pledgeable profits to 20% or 40% would not change qualitatively our conclusions.